ECONOMIC ANALYSIS OF A DEREGULATED POWER SYSTEM USING THE PROPORTIONAL TRACING METHOD

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By

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DISSERTATION

Submitted to the Electrical & Electronics Engineering Programme
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CERTIFICATION OF APPROVAL

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June 2010

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

Lee Tze Yang

ABSTRACT

Continuing trend towards deregulation and unbundling of transmission services has resulted in the need to measure the flow of power primarily for pricing and tariff purposes. Tracing methodology hence had been introduced to overcome problems related to the Marginal pricing of transmission costs. This study is twofold: the first revolves around the validation of the method and a 360^0 analysis of the proportional method which leads to a redefined power tracing method; the second is to further refine the proposed prediction method in [1] by establishing trends of the learning coefficients, using them to examine the relationship between accuracy and number of samples taken. Response of individual generators to change in demand and the corresponding associated losses are also presented. MATLAB with matpower4.0b extension was used to present the study on the IEEE 24bus RTS. Finally a real time amenable prediction tool using the regression method will be proposed.

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CHAPTER 1
INTRODUCTION

1.1 Deregulation and the Current Energy Market

Deregulation of the electric power industry started as early as 1996, where California begins to loosen controls on its energy market and takes measures to increase competition [2]. Similar to deregulation in any industry, this entailed in an increased competition in the electric power industry, which is now comprised of several players instead of the traditional monopoly by a single utility. This implies that consumers are presented with choices which would be determined by primarily price, reliability and quality of energy offered by respective retail company.

Our current energy market, in reference to Malaysia in particular is in the form of a monopoly, by our national utility, Tenaga Nasional Berhad. The market model is also referred to as a vertically integrated model with a one party rule over all the services, from generation to distribution and retailing, illustrated in the following diagram:

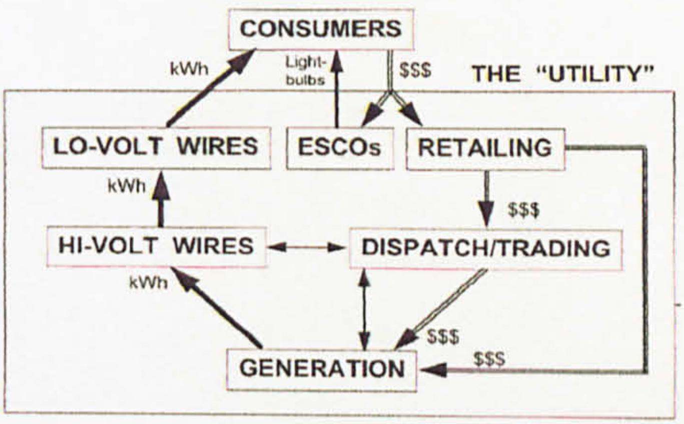

Figure 1 The Traditional Utility Structure [3]
Boxed up entities are the building blocks of an energy market, currently provided solely by the utility.

Introduction of the independent power producers (IPP) some years back introduced some form of service unbundling and competition, only at the generation end to the energy market. Nonetheless, the utility is still the regulating body governing the management of the system, i.e. energy unit price and generation level. This however did not contribute significantly to consumer's benefit.

A closer analysis of our energy system is seen to be a formation of several basic building blocks [3], i.e. the individual entities within the large box with the arrow showing the principal relationships among them (Figure1). Having this in mind, the following question is given a thought: what is the possibility of having individual competing companies in each of the entities, reprising the role played by the traditional utility in that specific area, but with those companies in competition with each other? In this way, a retail company can choose to perform business transaction with their preferred generation company, while even be able to choose the transmission company. Consumers in turn will have a choice of retailers to purchase energy from, instead of solely from the utility in the past. This is called the deregulated energy market model, which is governed by the law of demand and supply. Of course the proposition is not for a total free market, especially in its inception stage but with the existence of a regulating body overlooking all market activities, and limited deregulation for starters.

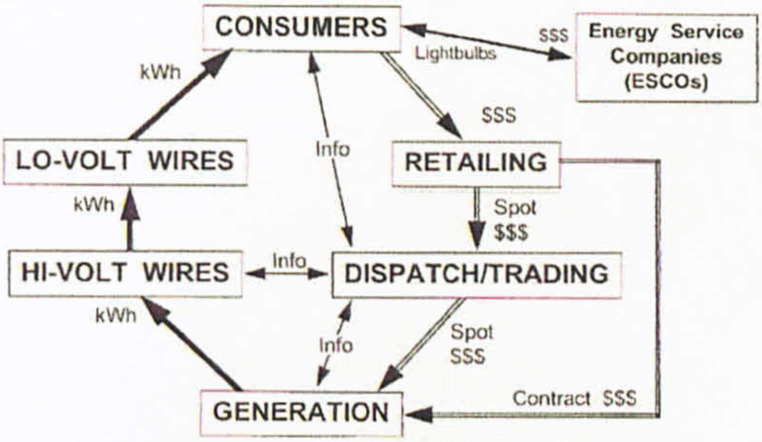

Figure 2 The deregulated market model [3]
Notice the introduction of the term Spot, Contract and Info in the above diagram, which will be the cornerstone of the following discussions.

Trend towards deregulation and unbundling of transmission services proliferated in the US and Europe with the rest of the world jumping onto the bandwagon. Electricity is now a commodity bought and sold by generators, retailers (suppliers) and other traders [4] to end consumers like home users and the industries. Cross-border trades are taking place even as of now in Europe, where a generator in Norway can be supplying power to Denmark [5]. No commodity can be traded however, unless there are appropriate arrangements for its delivery and pricing [3]. This is represented in Figure 2 by the 'Info' and 'Spot' arrows depicting this scenario of how energy is to be priced and delivered.

The coordination between the generation providers, transmission system operators (TSO) and retailers for technical operation of these sub entities and the commercial arbitration among them may be carried out by an independent system operator (ISO) for effecting power wheeling through agreed upon contract paths, while addressing vital attributes such as system security, voltage profile, losses and VAR reserves [1].

Electric power flow is undefined when transmitted via the Grid, which poses a major question in realization of the deregulation: how is the flow of electric power traced in order to justify a pricing system of electricity and also how is coordination done to ensure those sub entities still function as they do under a vertically integrated structure?

1.2 Problem Statement

Such tool which would still uphold the functionality of a deregulated market by providing vital information in implementing coordination is power tracing. It is essentially the tracking of power flow path, quantity and related losses to the particular transaction. There has not been one proven method which was thoroughly justified to provide sufficiently accurate information in filling the void of the 'Info' and 'Spot' arrows in Figure 2.

Deregulation not only reforms the way business transaction is performed in the energy market, but also the gencos' business strategy by only supplying sufficient power to meet the demand at a given point of time to prevent unrecovered generation cost. This is replicated in the retailers' approach by only purchasing sufficient power from these gencos to be sold to end users. However, all cost saving measures has to account for system reliability too because in any event of supply shortage, a possible major black out may be triggered. Prediction hence plays an even more crucial role in a deregulated market since no genco will be willing to generate power in excess than what is demanded. The question is now how to harness the information provided by any of those afore mentioned tracing methods in performing efficient forecasting in a deregulated energy market.

Keeping in mind that deregulation would be a success if and only if the interests of both customers and utilities are sustained, i.e. the market concept of electricity (supply and demand) prevails, providing consumers cheaper electricity, with upheld security of system.

1.3 Objectives & Scope of Study

The objective of the research will be to study existent power tracing methods [4, 6, 12, 19] to perform comparisons and to discern feasible methods which would ultimately contribute to the adoption of it towards the deregulation of the energy market. The Proportional Method [4] is single-handedly picked out and assessed, for the sole reason that it is the most established and exhaustively justified, which is envisioned to fill up the loopholes left by the Locational Marginal Pricing (LMP) method.

A simplification algorithm is proposed, which offers procedural standardisation and consistency of the method. Prediction using learning coefficients will be studied in the second part. Trends of the coefficients vs. number of samples taken will be analysed to prove the efficacy of the coefficients method in performing prediction. This project hence is twofold: first is providing the upstream and downstream algorithm with a more direct and straightforward approach, in terms of definitions and methodology, second is to establish the utilisation of learning coefficients in analysing the response of generators to change in demand with the associated losses in a deregulated energy market as an informative tool to market players in performing business related decisions.

Finally a real time amenable prediction tool using the regression method and the learning coefficients will be proposed.

CHAPTER 2
LITERATURE REVIEW

2.1 The Locational Marginal Pricing (LMP) and Its Shortcomings

The LMP is a market-pricing approach used to manage the efficient use of the transmission system to mitigate congestion in a transmission system. Marginal pricing is the idea that the market price of any commodity should be the cost of bringing to market, the last unit of that commodity which balances supply and demand. Hence for electricity, this marginal price may vary at different times and locations based on transmission condition [6].

LMP is currently the most employed method in establishing a pricing regime in a deregulated market system, also known as the nodal pricing method, which is highly volatile and provides perverse economic signals to the transmission company and fails to recover the incurred cost [7, 8]. The method of incremental loss based charging may become negative, resulting in a negative marginal cost of loss, encouraging consumers to increase demand but ironically pay lesser for that increase. Dependency on the location of the slack bus in the LMP method would render the fairness of charges to be questionable. An alternative used at the moment is a uniform pro-rata charge, although certain users might induce more loss in the transmission than others, relative to the transmission path taken.

Transmission pricing regime should promote competition by presenting the network users a predictable, stable and practical to apply framework of charges while the prices should also provide signals to towards the efficient use, operation and expansion of the network [9].

2.2 The Proportional Tracing Methodology

A relatively simple topological and straightforward method of tracing the flow of power in transmission network, known as the proportional tracing method is currently the most widely established and substantiated method amongst the few devised currently. This method can be used to allocate the charges for the reactive power, transmission services and transmission losses as well as the application of the method as a trading ground in cross border trades. Tracing methodologies have been proposed as an alternative to the LMP in devising a fairer pricing regime [10].

In contrary to common believe that electric power cannot be traced in a meshed network apart from the total current input and total current output at a node according to Kirchhoff's Current Law, J. Bialek et al [10] proved that the proportional method could be used to assess how much of the real and reactive power from a particular generator (station) goes to a particular load which simultaneously assesses the contribution of individual generators or loads to individual line flows. With this information, another algorithm was introduced, called the loss-apportioning which allows the breakdown of total transmission loss into components attributed to individual loads or generator. In this manner, justness is preserved where the load or generator pays for the losses it incurred through transmission, in layman's term: paying for what you've used (transmission service).

The concept revolves around Kirchhoff's Current Law, and ignoring the voltage law would not introduce any further errors as the law has already been used in obtaining the flow in power flow studies. The method suggests that in a meshed system with *n* nodes, *m* directed links and 2*m* flows, the output of a node *i* can be modelled as a pie chart with *n* portions, each supplied by the *n* number of input branches respectively. Consider the following network:

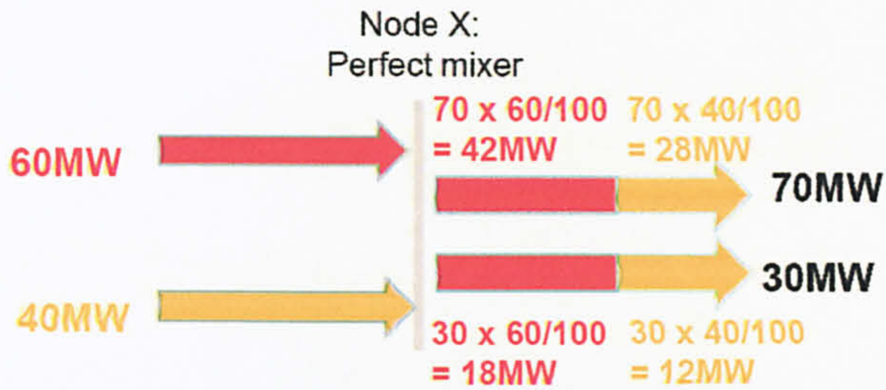

Figure 3 Proportional sharing principle

It can be said that the 70MW consists of 70 x 60/100 = 42MW supplied by the *red* line while 70 x 40/100 = 28MW supplied by the *yellow* line. The same can be stipulated for the 30MW line. Due to the nature that electricity is indistinguishable, it may be assumed that each MW leaving the node contains the same proportion of the inflows as the total nodal flow. Realisation of this method is done through two algorithms: the Upstream Algorithm which traces the gross flow (inflow) and the Downstream Algorithm which traces the net flow (outflow).

2.2.1 *Upstream Algorithm [10]*

The total flow P_i, the inflow to the i^{th} bus, is the sum of all the inflows through the lines connected to the bus and the local bus injection

$$P_i = \left(\sum_{j \in \eta} \left| P_{i-j} \right| \right) + P_{Gi} \quad \text{for } i = 1,2,\ldots n \tag{1}$$

where η is the set of nodes directly supplying node i, implying power flow towards i^{th} node. If the line losses are neglected, then $|P_{j-i}| = |P_{i-j}|$. Equation (1) can be further expanded to become:

$$\mathrm{P_i} = \left(\sum_{j \in \eta} \left| \frac{P_{j-i}}{P_j} P_j \right| \right) + \mathrm{P}_{Gi} \qquad \text{for i} = 1,2,\dots\text{n} \tag{2}$$

By defining $c_{ji} = |P_{j-i}|/P_j$ to express relationship between line flow and the nodal flow at the j^{th} node, using proportional sharing principle $|P_{j-i}| = c_{ji}\, P_j$, substituting this in (2) yields:

$$\left(\mathrm{P}_i - \sum_{j \in \eta} c_{ji} \mathrm{P}_j \right) = \mathrm{P}_{Gi} \quad \text{or} \quad \mathrm{A}_u \mathrm{P} = \mathrm{P}_G \tag{3}$$

P is the vector of gross nodal flows; P_G is the vector of nodal generations, while A_u is called the Upstream Matrix, which elements can be generalized as follow:

$$[\mathrm{A}_u]_{ij} = \begin{cases} 1 & \text{for } i = j \\ -c_{ji} = -\dfrac{|\mathrm{P}_{j-i}|}{\mathrm{P}_j} & \text{for } j \in \eta \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The i^{th} element of $\mathrm{P} = \mathrm{A}_u^{-1} \mathrm{P}_G$ shows the participation of the k^{th} generation to the i^{th} nodal flow and determines the relative participation of the nodal generations in meeting a retailer's demand, given by:

$$\mathrm{P}_i = \sum_{k=1}^{n} \left[\mathrm{A}_u^{-1} \right]_{ik} \mathrm{P}_{Gk} \quad \text{for } i = 1,2,\dots.n \tag{5}$$

Finally, load demand at the i^{th} bus, applying the proportional methodology is given by:

$$\mathrm{P}_{Li} = \frac{\mathrm{P}_{Li}}{\mathrm{P}_i} \mathrm{P}_i \quad \text{or}$$
$$\mathrm{P}_{Li} = \left(\frac{\mathrm{P}_{Li}}{\mathrm{P}_i} \sum_{k=1}^{n} \left[\mathrm{A}_u^{-1} \right]_{ij} \right) \mathrm{P}_{Gk} \quad \text{from} \quad i = 1,2,\dots n \tag{6}$$

Equation (6) shows the gross demand at node *i*. Share of the output of the i^{th} generator used to supply the k^{th} load demand at the point of generation is indicated by the respective *k–i* element of the A_u^{-1} matrix. It can be used to trace where the power of a generator goes to.

2.2.2 Downstream Algorithm [10]

The total flow P_i, the outflow to the i^{th} bus, is the sum of all the outflows through the lines connected to the bus and the local bus load

$$P_i = \left(\sum_{l \in \mu} \left| P_{i\text{-}\ell} \right| \right) + P_{Li} \qquad \text{for i} = 1,2,\ldots\text{n} \tag{7}$$

where μ is the set of nodes directly supplied from node *i*, implying power flowing from the i^{th} node. If the line losses are neglected, then $|P_{l\text{-}i}| = |P_{i\text{-}l}|$. Equation (7) can be further expanded into:

$$P_i = \left(\sum_{l \in \mu} \left| \frac{P_{l-i}}{P_{l}} P_l \right| \right) + P_{Li} \qquad \text{for i} = 1,2\ldots.,\text{n} \tag{8}$$

Defining $c_{li} = |P_{l\text{-}i}|/P_l$ expressing relationship between line flow and the nodal flow at the l^{th} node and using proportional sharing principle, $|P_{l\text{-}i}| = c_{li} P_l$. Substituting this in (8) yields

$$\left(P_i - \sum_{l \in \mu} c_{li} P_\ell \right) = P_{Li} \quad \text{or } A_d P = P_L \tag{9}$$

P is the vector of net nodal powers; P_L is the vector of nodal load demands, while A_d is called the Downstream Matrix, which elements can be generalized as follow:

$$\left[A_d\right]_{i\ell} = \begin{cases} 1 & \text{for } i = j \\ -c_{\ell i} = -\dfrac{\left|P_{\ell-i}\right|}{P_\ell} & \text{for } j \in \mu \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

The i^{th} element of $P = A_d^{-1}P_L$ shows the distribution of the i^{th} nodal power between all the loads in the system. In summation form,

$$P_i = \sum_{k=1}^{n} \left[A_d^{-1}\right]_{ik} P_{Lk} \qquad \text{for } i=1,2,....n \tag{11}$$

Finally, nodal generation as an inflow at the i^{th} bus, applying the proportional methodology is given by:

$$P_{Gi} = \frac{P_{Gi}}{P_i} P_i \text{ or}$$

$$P_{Gi} = \left(\frac{P_{Gi}}{P_i} \sum_{k=1}^{n} \left[A_d^{-1}\right]_{ij} \right) P_{Lk} \text{ from } i = 1,2,...n \tag{12}$$

Equation (12) shows the net generation at node i. Contribution of the k^{th} generator to the i^{th} load demand at the point of consumption is indicated by the respective i–k element of the A_d^{-1} matrix. It can be used to trace where the power of a specific load comes from.

2.2.3 Relevancy of the Proportional Tracing Methodology

The application of electricity tracing is to apportion losses to individual generators or loads. This can be done by accumulating the losses as the power flows to individual loads or from generators. The nodal loss is then assumed to be shared proportionally amongst loads (or generators) according to the proportional method or to the square of the outflows [10]. The worked out mathematics encompasses the logic in apportioning loss, which is not solely dependent on the load's power demand, but also the transmission path, as losses is proportional to the transmission distance which logically, the higher the losses, the higher the energy price will be.

Further establishing the rationale of proportional sharing, J.W. Bialek et al [4] pitches the proportional loss allocation to the square loss allocation (non proportional) demonstrating the loophole in the later, strengthening the rationality of the preceding despite well knowing that loss is proportional to the square of the current. Economics and mathematical concepts such as the game theory, Shapley value and the information theory [4] are evoked to strengthen the argument. The proportionality method thus has been painstakingly proven and demonstrated to be a viable tracing method. Relatively direct and simple, yet encompasses all aspects which would uphold fairness in determining pricing of electricity which is aggregation invariant.

In [9], Bialek mentioned that the results obtained using optimal tracing (includes congestion pricing) in comparison with uniform, which is the proportional tracing, does not increase societal welfare significantly (an increase of only 6% in the pricing). This is supported by [11] which the comparison of both methods only showed a little improvement of fairness with the optimal tracing. This suggests that a practical but not necessarily theoretically optimal methodology in power tracing is preferable to a theoretically optimal but complicated one [9].

2.3 Optimal Tracing Method: The Commons Method

Another issue heavily linked to power tracing is congestion management, where pricing derived from tracing based algorithm is always questioned to be reflective of the line condition at time of transmission or otherwise [12]. In [4], [5], [7], [9], [10], [13] and [14] there has been no citation of how the proportional tracing methodology could be used to address congestion. G.Strbac et. al [12] advocated that the conditions which lead to maximum flow is required to be determined, which then allocation of usage, where usage is apportioned among all the system users which contribute to the flow, should be done contingent to the conditions obtained. Maximum flow conditions require the consideration of a variety load levels and all contingencies within the security criteria [12] and are not to be attributed to solely peak load conditions. An algorithm is proposed to perform the identification of maximum flow conditions.

For each load level, which was optimally suggested to be six [12], a security constrained optimal dispatch is performed. No further explanation by the authors is given as to why six load levels are chosen. For each load level, under normal and contingency condition, flows in all branches are determined. The subroutine is reiterated until the maximum flow condition for each branch under the specific load and contingency situation has been found. The whole process is then repeated for a different load level with their respective contingencies. No method for contingency selection was proposed in the paper which leaves it open for interpretation. As a result, large number of contingencies is anticipated to be included for analysis, which will lead to long load flow calculation time. Finally, allocation of usage of the system by individual generators and loads is done at this stage, upon determining the contingency case which leads to maximum flow.

2.4 Prediction Using Learning Coefficients

The usage of learning coefficients in determining generators' optimal dispatch has been established in [15], by approximating the heat-rate curve of generator, shown below in *Figure 4* with a generalized quadratic relationship in the form of $H(P_G) = \alpha/P_G + \beta + \gamma P_G$ [15], where α, β and γ will be solved for respectively by simultaneous equation.

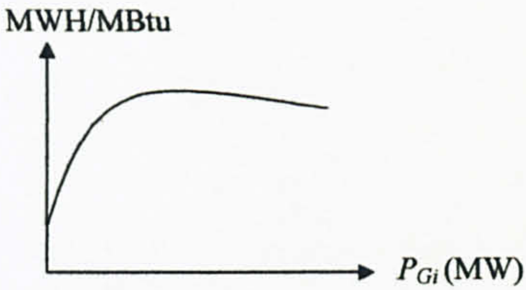

Figure 4 Generator Heat Rate Curve [15]

The postulation to qualify the evocation of this method is the direct relationship of all the mentioned quantities to the power generated and cost (of generation). Essentially, the governing factor of price per unit of energy is the fuel consumption of the generator in supplying the demanded power, which is governed by the heat rate curve. Transmission losses is tacit within generated power for the reason that power supplied has to meet the demand of retailers, inclusive of losses. It is also straight forward that the greater the power demanded, the greater the generation level will be and subsequently the losses too, up to an allowable limit when no extra generation can take place, as observed from the heat rate curve.

This is extended to the prediction of the (i) share of generations meeting a retailer's demand, (ii) retailers demand and the power loss in a transaction, (iii) a retailers demand and the share of the part transactions in a line and (iv) a retailer's demand and the losses pertaining to each of the transactions in a line. All the relationships assume the form of the aforementioned heat-rate curve of a generator.

Four types of learning coefficients $(\alpha_1,\beta_1,\gamma_1)$, $(\alpha_2,\beta_2,\gamma_2)$, $(\alpha_3,\beta_3,\gamma_3)$, and $(\alpha_4,\beta_4,\gamma_4)$, need to be generated at each demand node of the network. Thus, there will be $(ng\times npq)$ sets of $(\alpha_1,\beta_1,\gamma_1)$, $(ng\times npq)$ sets of $(\alpha_2,\beta_2,\gamma_2)$, $(ng\times npq\times nl)$ sets of $(\alpha_3,\beta_3,\gamma_3)$, and $(ng\times npq\times nl)$ sets of $(\alpha_4,\beta_4,\gamma_4)$ to be generated using real time operating scenarios, during learning exercise, where '*ng*' represents number of generations, '*npq*' represents number of retail or demand points and '*nl*' represents number of active links in an operating scenario.

2.4.1 *Learning relationship between a generator's contribution to a retailer's demand at the receiving end*

$$\frac{\alpha_1}{P_d} + \beta_1 + \gamma_1 P_d = P_{gd} \tag{13}$$

Where P_d is the total demand at a retailer's point of receipt in per unit (p.u.), P_{gd} is a generator's contribution to a retailers demand at the point of receipt in p.u.

This equation presents a relationship of the generator's end generated power to the power demanded where P_{gd} is the dependent variable and P_d is the independent variable.

2.4.2 *Learning relationship between a retailer's demand and the associated loss in a transaction*

$$\frac{\alpha_2}{P_d} + \beta_2 + \gamma_2 P_d = Loss_t \tag{14}$$

Where P_d is the total demand at a retailer's point of receipt in p.u., $Loss_t$ is loss in a transaction in p.u. (The difference between a generation's contribution to a demand at the generation end and a generation's contribution to a demand at the load bus, which is the result of the Sending Algorithm less the result of Receiving Algorithm for the same generator and load).

This equation presents a relationship of the transmission loss incurred supplying a given load in the system to the power demanded where P_{gd} is the dependent variable and P_d is the independent variable.

2.4.3 *Generation of the coefficients*

For improved credibility in the learning coefficients, a higher number of samples are to be used. As a rule of thumb, a minimum of 3 samples suffices for the generation of a set of learning coefficients: Three unknowns require a minimum of three samples for the generation of one set of learning coefficients. The four equations presented above can then be solved respectively, in matrix form:

$$\begin{bmatrix} \alpha_1 \\ \beta_1 \\ \gamma_1 \end{bmatrix} = \begin{bmatrix} \frac{1}{P_{d1}} & 1 & P_{d1} \\ \frac{1}{P_{d2}} & 1 & P_{d2} \\ \frac{1}{P_{d3}} & 1 & P_{d3} \end{bmatrix}^{-1} \begin{bmatrix} P_{gd1} \\ P_{gd2} \\ P_{gd3} \end{bmatrix} \tag{15}$$

$$\begin{bmatrix} \alpha_2 \\ \beta_2 \\ \gamma_2 \end{bmatrix} = \begin{bmatrix} \frac{1}{P_{d1}} & 1 & P_{d1} \\ \frac{1}{P_{d2}} & 1 & P_{d2} \\ \frac{1}{P_{d3}} & 1 & P_{d3} \end{bmatrix}^{-1} \begin{bmatrix} Loss_{t1} \\ Loss_{t2} \\ Loss_{t3} \end{bmatrix} \tag{16}$$

As the number of samples increases, the learning coefficients will be determined using the regression method, where $x = (A^T A)^{-1} A^T b$ for matrices or the form $Ax = b$. Addition of samples will elicit a row addition to the A and b matrices, changing the dimensions to a rectangular matrix.

CHAPTER 3
METHODOLOGY

3.1 Procedure Identification

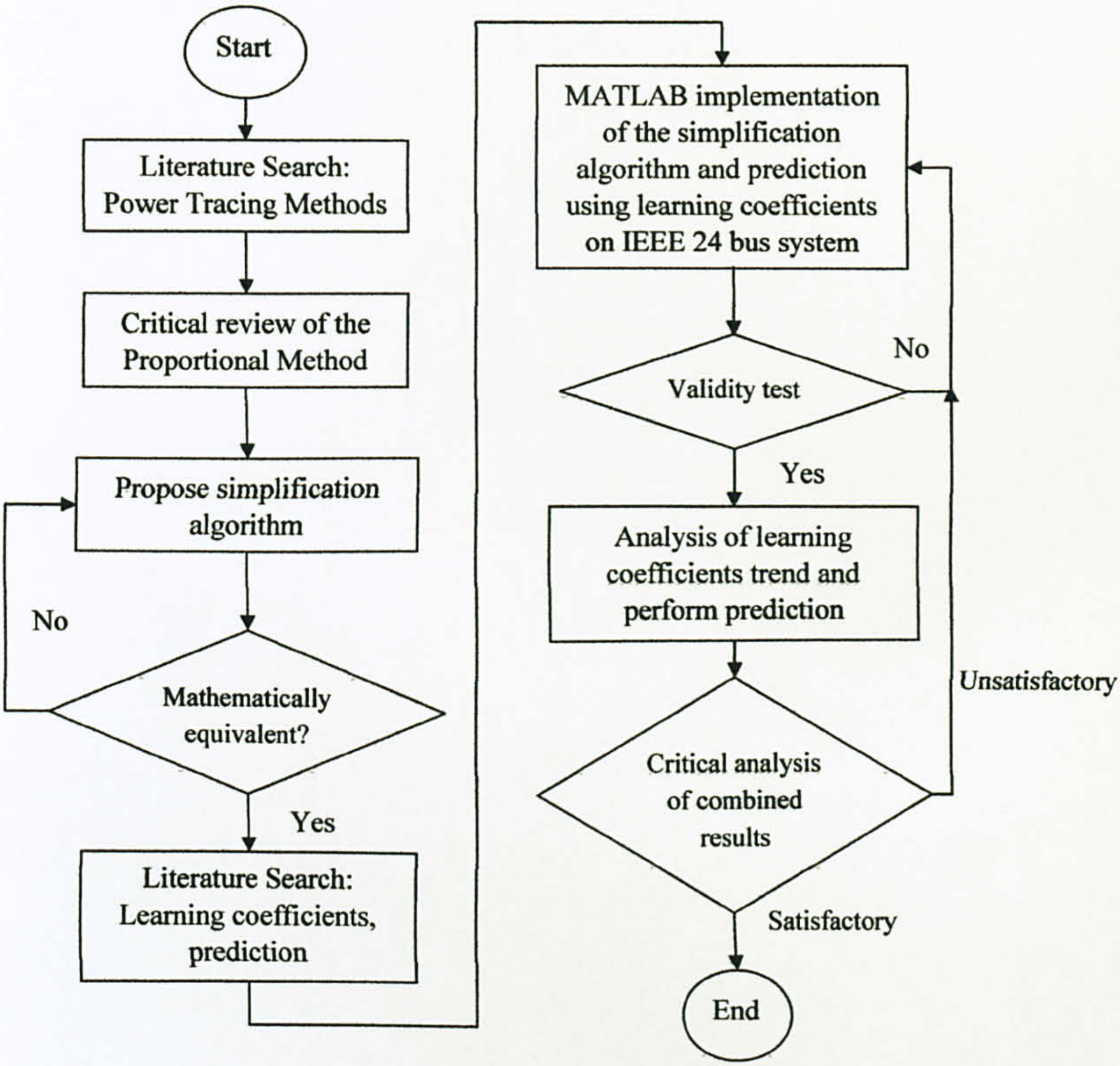

Figure 5 Process flow of project, from FYP I to II

The first part of the project is geared towards the familiarization of the deregulated energy market, power tracing concept, methods, and application. After identifying proportional tracing methodology as the method to build on, its strengths and weaknesses are analysed, leading to the inception of the Simplified Algorithm, this is detailed in the Results and Discussion section.

Building on the application of the tracing methodology in the deregulated energy market, issues such as congestion management, ATC and prediction are studied. The prediction methodology proposed in [1] was analysed, with several areas identified for refinements. MATLAB implementation of the tracing methodology is first implemented. The results are then verified manually to be mathematically correct. Modification is then done to the M-File to evoke the Simplified Algorithm instead. The results are then cross referenced with that of the original Proportional Methodology. For simplicity purposes, a four bus test system is used as input data to perform tracing. Upon verification, the programme is then tested on the IEEE 24 bus RTS [16]. Only upon ascertaining the credibility of the M-File, implementation of the prediction method through calculation of learning coefficients is done.

The challenge in the implementation of the learning coefficient method is the data handling and addressing in the M-File, due to the sheer amount of learning coefficients to be dealt with, as described in the Literature Review section. Hence for purpose of clarity and simplicity, only one relationship was picked to be examined, which is the relationship between a generator's contribution to a retailers demand at the receiving end. Prior to implementation in MATLAB, careful attention is given to efficient manipulation and handling of data using matrices to produce a minimal execution time M-File coding. One set of learning coefficients is generated and the data plotted on graphs to analyse the trend.

Only upon establishing a relationship and reasoning to the trends, the relationship between a retailer's demand and the associated loss in a transaction is analysed. Load hourly demand for week 1 to week 52 presented in [16] is used as data source to perform all mentioned studies.

Next, the short term prediction of the oncoming demand using the learning coefficients is done. This section involves in depth analytical and critical review of the learning coefficient and the regression method to devise a prediction algorithm, where no previous references exist. The performance of the devised prediction method is gauged in terms of the mean absolute percentage error (MAPE) defined below:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|Actual(i)-Forecast(i)|}{Actual(i)} \times 100 \qquad (17)$$

In general, a MAPE of 10% is considered good, while a MAPE in the range 20% - 30% or even higher is quite common [17]. Hence the acceptance criterion for the prediction method is set to an MAPE of below 10%. Trial and error was done continuously until the criterion is satisfied.

Lastly, all the individual sub routines are integrated into a fully automated programme which would prompt the user for the load ID, week and hour of the day to be predicted. Upon receiving the required input, the programme will run and display the primary result first: the predicted demand in p.u. with the option to either display or suppress subsequent intermediate results, where the programme ends by displaying the estimated breakdown of power anticipated to be supplied by respective generators in the system and the associated losses for the predicted power of the particular load.

3.2 Actual and Planned Project Time Line

The overall progress of the project is on time, with actual progress quicker than planned. All that is left in this completion phase of project is proper documentation of all work done. Also, the preparation of conference paper is brought forward instead of planned, in conjunction with the 4th International Power Engineering and Optimization Conference, where the conference paper has been prepared and submitted as a proceeding to the mentioned conference. Project Gantt Chart is presented in Appendix A.

3.3 Tools

MATLAB is the sole software required. All simulations are carried out by first writing the codes in M-Files. The MatPower extension to MATLAB, developed by the Power Systems Engineering Research Centre (PSERC) is used to perform load flow in written M-Files. The MatPower extension is free for download from PSERC's homepage.

Other indispensible resources are Bialek's conference papers on the Proportional Tracing methodology and the book entitled Power Generation, Operation and Control by Allen J. Wood and Bruce F. Wollenberg.

The IEEE Reliability Test System file [16] which contains all load and generation data for the 24 bus IEEE Reliability Test System is used to obtain the detailed line, load and generator data. Of the 15 tables in the documentation, tables 1, 2, 3, 4, 5 and 7 were used. Tables 2, 3, 4, 5 were used in conjunction with Table 1 to provide specific load demand at all load buses for a given time of a day in a given week of the year.

3.4 Algorithm of the Prediction Programme

The prediction programme first prompts for the load ID, week and hour to be predicted. Prediction results with percentage error will be displayed, along with a graphical representation of the prediction done. Programme will then wait for prompt from user to hit any key to continue.

It will continue to perform load flow and tracing, using the Sending and Receiving Algorithm for all the hourly demand data used to perform prediction in the preceding section, i.e. if previous 5 hours of demand is used to predict the oncoming demand, load flow and tracing will be conducted for all 5 hours respectively. Once completed, trends of generated power or trends of associated losses can be displayed on 3 graphs, each plotting the trend of respective α, β *and* γ vs. number of samples for all generators in the system.

A choice of displaying nothing can be selected if analysis of trends is not of interest at the moment. Finally, the programme will calculate using the learning coefficients obtained, the estimated values of generation and the associated losses in meeting the predicted oncoming demand. The overall process flow is illustrated in the form of a flow diagram overleaf.

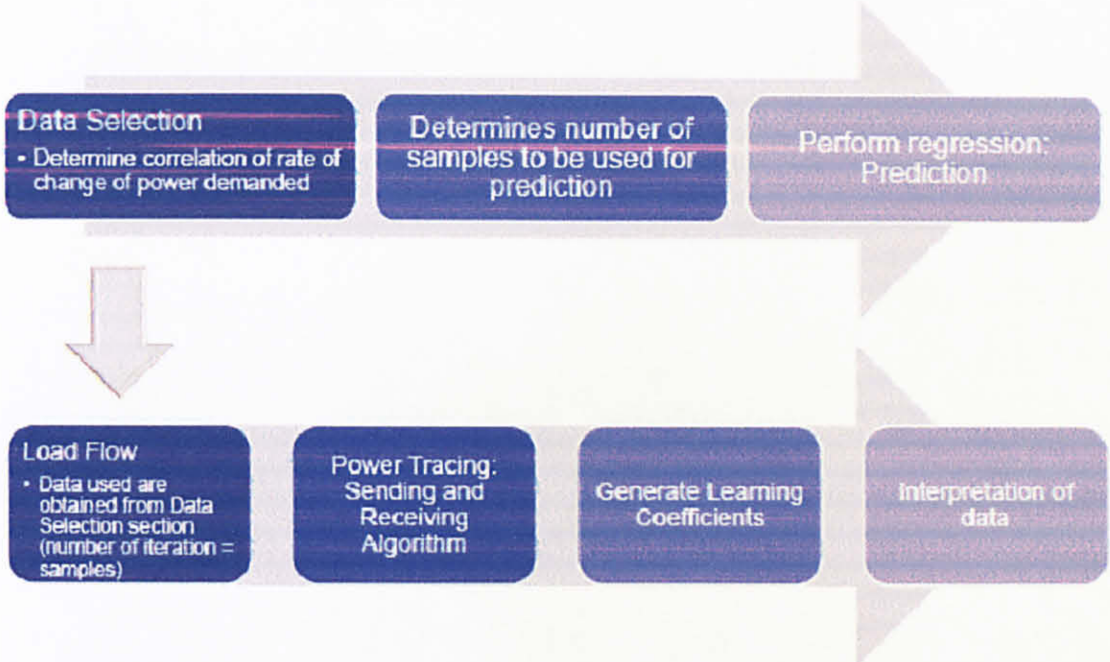

Figure 6 Flow Chart of the Prediction Programme

CHAPTER 4
RESULTS AND DISCUSSION

4.1 The Sending and Receiving Algorithms

The prime purpose of power tracing is to allocate losses associated with a particular transaction which then allows the determination of transmission pricing. These have been presented over the works of Bialek, often implicitly. It was demonstrated how the method could determine loss allocation to either generator or load. Bialek further went on employing the Downstream and the Upstream method to allocate loss and transmission usage. Also, the robustness of the method in yielding results when applied on a system with cyclic flow was demonstrated.

It would be desirable to implement the Proportional Method in a more straight forward manner whereby it could be understood even by laypeople for transparency especially in pricing matters. The benefit of having a method which resembles the condition of the power system would also be ease of results interpretation. This is in specific reference to both the Upstream and Downstream matrices which are to be formed by merely using the power flow data of the system. The ability to directly relate the matrix elements to the matrices would allow direct interpretation of data. Also consistency in the representation of row and column of those matrices would eliminate confusions or possible errors. It is foreseen in a real time implementation, computing efficiency is of utmost importance, where the shortest calculation time is desirable.

In an attempt to imbue the upstream and downstream algorithms with the afore-mentioned qualities, the Sending and Receiving algorithms were conceived. The concept is demonstrated on the same 4 bus test system used in [10] shown below.

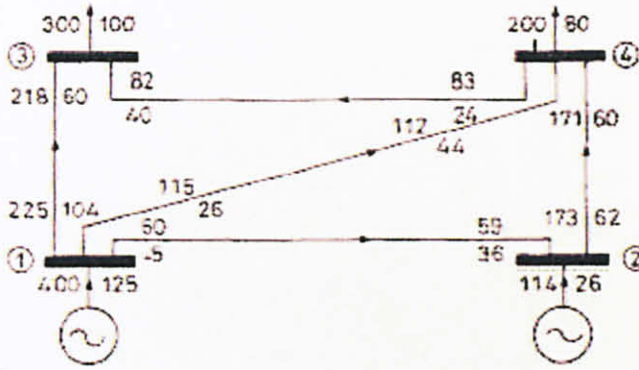

Figure 7 4 bus test system, from [10]

For the 4 bus test system shown, the nodal power balance equation for bus 1 is

$$\frac{P_{11}}{P_1}P_1 - \frac{P_{12}}{P_2}P_2 - \frac{P_{13}}{P_3}P_3 - \frac{P_{14}}{P_4}P_4 = P_{G1}$$

Where $\frac{P_{ii}}{P_i}P_i$ is the power level of bus i and it represents the diagonal elements in the A_u matrix which are substituted with 1 for the following reasons:

- Maintain a non singular matrix to ensure invertibility
- To keep the power flow equation balanced

What was tacitly done was the following:

$$\frac{P_{ii}}{P_i}P_i - \sum_{\substack{j\epsilon\alpha_i^{(u)} \\ j\neq i}} \frac{P_{ij}}{P_j}P_j = P_{G1}$$

Where the power outflow from bus i subtracted from the bus power level (sum of all inflows) is equivalent to the power generated at bus i.

Putting the above equation into matrix form for a 4 bus system:

$$\begin{bmatrix} \frac{P_1}{P_1} & \frac{-P_{12}}{P_1} & \frac{-P_{13}}{P_1} & \frac{-P_{14}}{P_1} \\ \frac{-P_{21}}{P_2} & \frac{P_2}{P_2} & \frac{-P_{23}}{P_2} & \frac{-P_{24}}{P_2} \\ \frac{-P_{31}}{P_3} & \frac{-P_{32}}{P_3} & \frac{P_3}{P_3} & \frac{-P_{32}}{P_3} \\ \frac{-P_{41}}{P_4} & \frac{-P_{42}}{P_4} & \frac{-P_{43}}{P_4} & \frac{P_4}{P_4} \end{bmatrix} \begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ P_4 \end{bmatrix} = \begin{bmatrix} P_{G1} \\ P_{G2} \\ P_{G3} \\ P_{G4} \end{bmatrix}$$

Factorizing the common denominator out,

$$\begin{bmatrix} P_1 & -P_{12} & -P_{13} & -P_{14} \\ -P_{21} & P_2 & -P_{23} & -P_{24} \\ -P_{31} & -P_{32} & P_3 & -P_{34} \\ -P_{41} & -P_{42} & -P_{43} & P_4 \end{bmatrix} \begin{bmatrix} P_1 & & & \\ & P_2 & & \\ & & P_3 & \\ & & & P_4 \end{bmatrix}^{-1} \begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ P_4 \end{bmatrix} = \begin{bmatrix} P_{G1} \\ P_{G2} \\ P_{G3} \\ P_{G4} \end{bmatrix}$$

Defining the left most matrix as the Sending Matrix, A_s where for a given element of the matrix P_{ij}, the column, j represents the sending bus while row, i represents the receiving bus. In congruence to the definition of the Upstream matrix, this matrix describes how much power bus j is contributing to bus i.

The second matrix after the Sending Matrix is called the inverse nodal through flow power, which is sum of either the inflow or the outflow. The third matrix from the left is the gross power flow matrix and the matrix on the right side of the equation is the generation matrix. Using the test system shown in *Figure 8*,

$$\begin{bmatrix} 400 & 0 & 0 & 0 \\ -60 & 173 & 0 & 0 \\ -225 & 0 & 300 & -83 \\ -115 & -173 & 0 & 283 \end{bmatrix} \begin{bmatrix} 400 & 0 & 0 & 0 \\ 0 & 173 & 0 & 0 \\ 0 & 0 & 300 & 0 \\ 0 & 0 & 0 & 283 \end{bmatrix}^{-1} \begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ P_4 \end{bmatrix} = \begin{bmatrix} P_{G1} = 400 \\ P_{G2} = 114 \\ P_{G3} = 0 \\ P_{G4} = 0 \end{bmatrix}$$

Solving the equation above:

$$\begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ P_4 \end{bmatrix} = \begin{bmatrix} 400 & 0 & 0 & 0 \\ 0 & 173 & 0 & 0 \\ 0 & 0 & 300 & 0 \\ 0 & 0 & 0 & 283 \end{bmatrix} \begin{bmatrix} 400 & 0 & 0 & 0 \\ -60 & 173 & 0 & 0 \\ -225 & 0 & 300 & -83 \\ -115 & -173 & 0 & 283 \end{bmatrix}^{-1} \begin{bmatrix} 400 \\ 114 \\ 0 \\ 0 \end{bmatrix}$$

Evaluating A_S^{-1},

$$A_S^{-1} = \begin{bmatrix} 400 & 0 & 0 & 0 \\ -60 & 173 & 0 & 0 \\ -225 & 0 & 300 & -83 \\ -115 & -173 & 0 & 283 \end{bmatrix}^{-1} = 10^{-3} \begin{bmatrix} 2.5 & 0 & 0 & 0 \\ 0.86705 & 5.7803 & 0 & 0 \\ 2.3027 & 0.97762 & 3.333 & 0.97762 \\ 1.5459 & 3.5536 & 0 & 3.5336 \end{bmatrix}$$

$$\therefore \begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ P_4 \end{bmatrix}_{gross} = \begin{bmatrix} 400 & 0 & 0 & 0 \\ 0 & 173 & 0 & 0 \\ 0 & 0 & 300 & 0 \\ 0 & 0 & 0 & 283 \end{bmatrix} \begin{bmatrix} 1 \\ 1.0058 \\ 1.0325 \\ 1.0212 \end{bmatrix}$$

Loss factor matrix
(loss attributed to load)

Attributing losses to individual loads,

$$L_3 = (loss\ factor_3 - 1) \times P_{L3} = (1.0325 - 1) \times 300 = 9.75MW$$

$$L_4 = (loss\ factor_4 - 1) \times P_{L4} = (1.0212 - 1) \times 200 = 4.24MW$$

which sums to 14MW of losses attributed to loads in the system. Further attributing losses to loads in respect to the generators contribution to respective load's demand:

Table 1 Breakdown of generator's contribution to load's demand

	G1	G2	Total	Loss
L3	$A_S^{-1}(3,1) \times P_{L3} \times P_{G1}$ $= 2.3027\text{x}10^{-3}\text{x } 300 \text{ x } 400$ $= 276.32$	$A_S^{-1}(3,2) \times P_{L3} \times P_{G2}$ $= 0.97762\text{x}10^{-3}\text{x } 300 \text{ x } 114$ $= 33.43$	309.75	9.75
L4	$A_S^{-1}(4,1) \times P_{L4} \times P_{G1}$ $= 1.5459\text{x}10^{-3}\text{x } 200 \text{ x } 400$ $= 123.68$	$A_S^{-1}(4,2) \times P_{L4} \times P_{G2}$ $= 1.5459\text{x}10^{-3}\text{x } 200 \text{ x } 114$ $= 80.56$	204.24	4.24
Total	400	114	514	14

The whole algorithm to some point has been made intuitive with a more direct relation to the nature of a power system – the Sending Matrix was formed by only mere inspection of the power flow.

Also, observe in the above table that the rows and columns corresponds to a systematic coordinate system, where the calculation of loss requires the (x,y) element of the A_S^{-1} matrix multiplied by the power of generator and load in interest.

The same could be done to the Downstream algorithm too, but instead of a downstream matrix, a receiving matrix, A_r is formed. Using the similar test system,

$$\begin{bmatrix} 400 & -59 & -218 & -112 \\ 0 & 173 & 0 & -171 \\ 0 & 0 & 300 & 0 \\ 0 & 0 & -82 & 283 \end{bmatrix} \begin{bmatrix} 400 & 0 & 0 & 0 \\ 0 & 173 & 0 & 0 \\ 0 & 0 & 300 & 0 \\ 0 & 0 & 0 & 283 \end{bmatrix}^{-1} \begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ P_4 \end{bmatrix} = \begin{bmatrix} P_{L1} = 0 \\ P_{L2} = 0 \\ P_{L3} = 300 \\ P_{L4} = 200 \end{bmatrix}$$

$$\begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ P_4 \end{bmatrix}_{net} = \begin{bmatrix} 400 & 0 & 0 & 0 \\ 0 & 173 & 0 & 0 \\ 0 & 0 & 300 & 0 \\ 0 & 0 & 0 & 283 \end{bmatrix} \begin{bmatrix} 400 & -59 & -218 & -112 \\ 0 & 173 & 0 & -171 \\ 0 & 0 & 300 & 0 \\ 0 & 0 & -82 & 283 \end{bmatrix}^{-1} \begin{bmatrix} 0 \\ 0 \\ 300 \\ 200 \end{bmatrix}$$

A_r takes the transpose form of the A_s matrix, but is derived from the power received by bus j from bus i. Upon solving,

$$\begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ P_4 \end{bmatrix}_{net} = \begin{bmatrix} 400 & 0 & 0 & 0 \\ 0 & 173 & 0 & 0 \\ 0 & 0 & 300 & 0 \\ 0 & 0 & 0 & 283 \end{bmatrix} \begin{bmatrix} \boxed{0.9693} \\ \boxed{0.9849} \\ 1 \\ 0.9965 \end{bmatrix}$$

Boxed up are the factor of generator's useful power, where multiplied with the generator's generation level produces the actual power available to loads, after accounting for transmission losses. Attributing losses to generators:

$$G_1: (1 - 0.9693) \times 400 = 12.28\ MW$$

$$G_2: (1 - 0.9849) \times 114 = 1.71\mathrm{MW}$$

which sums to 14MW of total losses attributed to generators. Notice that the total loss here is equivalent to that found from the Sending Algorithm.

Since we are more interested in looking at loss incurred by a generator supplying a particular load (generator's point of view), a sub algorithm, dubbed the Loss Tracing is proposed utilizing the two sending and receiving matrices:

$$A_S^{-1} - (A_r^{-1})^T = A_{L(G)}$$

Where $A_{L(G)}$ is the loss matrix from the generator's point of view. A_r^{-1} is transposed to transform the shape of the matrix to mimic that of A_S^{-1} where the 2 matrices now carry a common convention where the column represents the sending bus while row represents the receiving bus. Also, $A_{L,G}$ is always a positive matrix.

Continuing the demonstration on the 4 bus system in Figure 8 with the found A_S^{-1} and A_r^{-1},

$$A_{L(G)} = 10^{-5}\begin{bmatrix} 0 & 0 & 0 & 0 \\ 1.4451 & 0 & 0 & 0 \\ 7.4792 & 2.2944 & 0 & 1.1779 \\ 4.1361 & 4.0851 & 0 & 0 \end{bmatrix}$$

Further apportioning losses with respect to the transactions of the system,

Table 2 Loss apportioning to respective generators and loads

	G1	G2	Total
L3	$A_{L(G)}^{-1}(3,1) \times P_{L3} \times P_{G1}$ $=7.4792\times10^{-5}\times300\times 400$ $= 8.975$	$A_{L(G)}^{-1}(3,2) \times P_{L3} \times P_{G2}$ $= 2.2944\times10^{-5}\times300 \times114$ $= 0.7847$	9.76
L4	$A_{L(G)}^{-1}(4,1) \times P_{L4} \times P_{G1}$ $=4.1361\times10^{-5}\times200\times 400$ $= 3.31$	$A_{L(G)}^{-1}(4,2) \times P_{L4} \times P_{G2}$ $=1.5459\times10^{-3}\times200 \times114$ $= 0.93$	4.24
Total	12.28	1.71	14

Notice the table takes the same form as that of the Sending Algorithm with the same reference convention (row and column of table to the row and column of matrix).

Data interpretation has been made more explicit with close relations to the condition of the power system under analysis. This improvisation is more convenient and less confusing with one convention used – for a given element P_{ij} of the A_S matrix, the column, j represents the sending bus while row, i represents the receiving bus, while the A_r takes the transpose form of A_S.

A common matrix, which is the bus power level matrix, is created while changes only apply to the flow related matrices (Sending and Receiving). The decomposed final solution gives revelation to the loss factor of generators or loads, an easy way to assess extent of use of the system by either generator or load.

This method has been tested on the IEEE 24 bus RTS and the results cross referenced with that of the original Upstream and Downstream Algorithms. The Sending and Receiving Algorithm yielded close matching results, with significant improvement seen in the calculation of losses where addressing of matrices has been made simpler by using only a single nested 'for' loop structure.

4.2 Learning Coefficients as a Prediction Tool

4.2.1 Preamble

While the main objective of the second part of the project is to establish a real time amenable prediction tool using the learning coefficients, the accuracy of the method in performing prediction is first examined through the trends of the learning coefficients generated with increasing number of samples employed. The process in ascertaining this fact also led to the discovery of greater implications of the trends with regards to the behaviour of generators and the associated losses in the system in response to increase in demand.

The information obtained from the analysis would prove to be useful in a deregulated system for operators to make informed decisions in regards to the natural response of the power system for optimal operating conditions of the system under external influence (power purchasing decisions) by the retailers.

4.2.2 Trends Analysis and the Learning Coefficients

Load at bus 8 was chosen as load under inspection for prediction to be done, primarily for the reason of its remote location from most of the generators in the 24 bus system. Learning coefficients generation is to be performed specific to the day of the week in a particular season. Monday of the winter weeks: week 52 and 8 is selected at random. Subsequently, 5 samples are selected by choosing 5 random hours within the day of week 52, with the same done for the Monday in week 8.

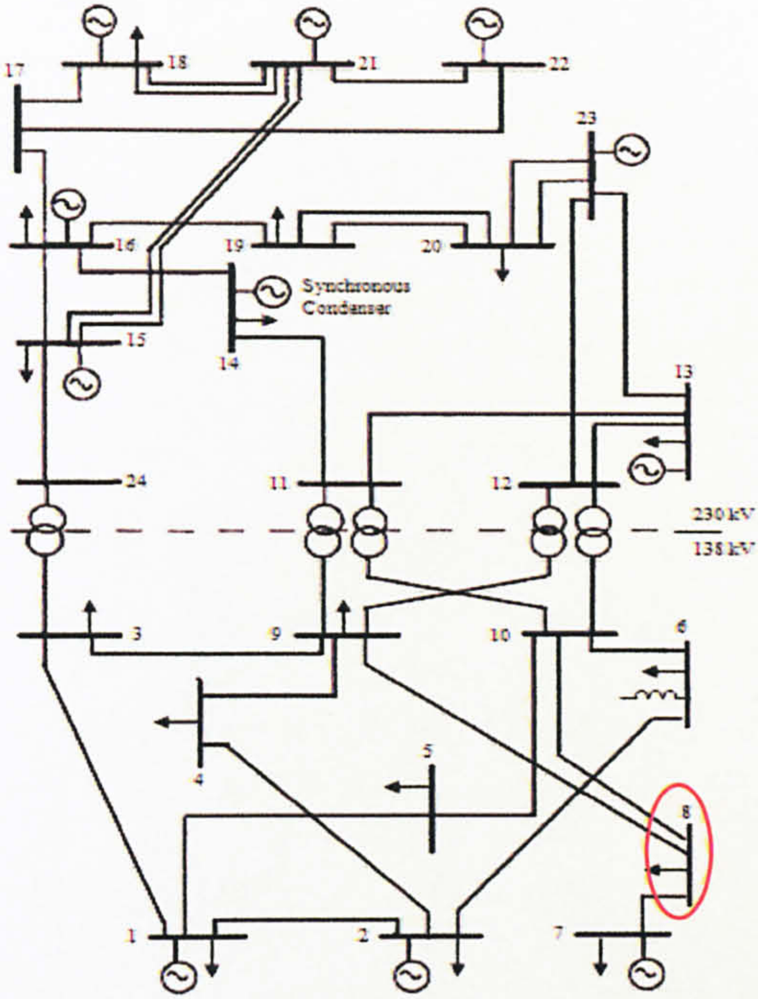

Figure 8 IEEE 24 bus Reliability Test System [16]

The 5 samples of the day are to be handpicked such that they reflect diverse load demands within a day, hence as a rule of thumb, no two consecutive hours are to be selected. Alternatively, the hours can be handpicked by emulating the 5 various time of day: midnight, beginning of office hours, midday, office dismissal hour and evening for a fair day/night hours representation. Such procedure is to ensure robustness of the learning coefficients since they are greatly influenced by the spread of the samples picked.

The order in which the samples are presented too, has a say on the values of the learning coefficients obtained. No predefined order exists or can be referenced to, hence at the time of simulation, a zigzag pattern is chosen as such, arranged from sample 1 to 10 for winter weeks: week52, 12-1am; week8, 2-3am; week52, 4-5am; week8, 7-8am; week52, 8-9am; week8, 10-11am; week52, 2-3pm; week8, 4-5pm; week52, 7-8pm; week8 9-10pm. The order of the sample points is illustrated in the table below.

Table 3 Order of data picked for coefficient generation for winter weeks

Hour\Week	**52**	**8**	**Hour\Week**	**52**	**8**
12-1 am	111.5793	94.46732	**noon-1pm**	158.2094	133.9462
1hr -2hr	104.9178	88.82748	**1hr-2hr**	158.2094	133.9462
2hr-3hr	99.92173	84.5976	**2hr-3hr**	154.8787	131.1263
3hr-4hr	98.25637	83.18764	**3hr-4hr**	156.544	132.5362
4hr-5hr	98.25637	83.18764	**4hr-5hr**	164.8709	139.586
5hr-6hr	99.92173	84.5976	**5hr-6hr**	166.5362	140.996
6hr-7hr	123.2368	89.96804	**6hr-7hr**	166.5362	140.996
7hr-8hr	143.2211	104.5575	**7hr-8hr**	159.8748	135.3562
8hr-9hr	158.2094	133.9462	**8hr-9hr**	151.548	128.3064
9hr-10hr	159.8748	135.3562	**9hr-10hr**	138.2251	117.0267
10hr-11hr	159.8748	135.3562	**10hr-11hr**	121.5714	102.9271
11-noon	158.2094	133.9462	**11hr-12hr**	104.9178	88.82748

Following ten tables are the results of the sending and receiving algorithm for the selected sample points:

Table 4 week52, 12-1am, demanded power = 111.5793MW

Gen	Gen End	Retail End	Loss
1	0.0000	0.0000	0.0000
2	0.0000	0.0000	0.0000
7	106.4663	104.5743	1.8921
13	0.4385	0.4336	0.0048
15	0.3627	0.3503	0.0124
16	0.5927	0.5724	0.0203
18	0.5528	0.5265	0.0262
21	0.6481	0.6173	0.0308
22	0.7983	0.7501	0.0482
23	3.8837	3.7547	0.1290
	113.7430	**111.5793**	**2.1637**

Table 5 week8, 2-3am, demanded power =84.5976MW

Gen	Gen End	Retail End	Loss
1	0.0000	0.0000	0.0000
2	0.0000	0.0000	0.0000
7	86.1144	84.5976	1.5168
13	0.0000	0.0000	0.0000
15	0.0000	0.0000	0.0000
16	0.0000	0.0000	0.0000
18	0.0000	0.0000	0.0000
21	0.0000	0.0000	0.0000
22	0.0000	0.0000	0.0000
23	0.0000	0.0000	0.0000
	86.1144	**84.5976**	**1.5168**

Table 6 week52, 4-5am, demanded power = 98.2564MW

Gen	Gen End	Retail End	Loss
1	0.0000	0.0000	0.0000
2	0.0000	0.0000	0.0000
7	99.1630	97.4092	1.7538
13	0.0442	0.0438	0.0004
15	0.0441	0.0427	0.0014
16	0.0731	0.0708	0.0024
18	0.0682	0.0651	0.0031
21	0.0791	0.0755	0.0036
22	0.0982	0.0924	0.0057
23	0.4714	0.4568	0.0147
	100.0414	**98.2564**	**1.7850**

Table 7 week8, 7-8am, demanded power = 104.5575MW

Gen	Gen End	Retail End	Loss
1	0.0000	0.0000	0.0000
2	0.0000	0.0000	0.0000
7	102.7191	100.8985	1.8206
13	0.2086	0.2066	0.0020
15	0.1900	0.1838	0.0062
16	0.3128	0.3025	0.0103
18	0.2918	0.2784	0.0134
21	0.3400	0.3243	0.0157
22	0.4205	0.3957	0.0248
23	2.0323	1.9678	0.0646
	106.5150	**104.5575**	**1.9575**

Table 8 week52, 8-9am, demanded power = 158.2094MW

Gen	Gen End	Retail End	Loss
1	0.0000	0.0000	0.0000
2	0.0000	0.0000	0.0000
7	115.0000	112.9032	2.0968
13	4.7828	4.6754	0.1073
15	1.8760	1.7912	0.0848
16	3.7387	3.5705	0.1682
18	3.4788	3.2769	0.2019
21	3.4877	3.2843	0.2035
22	4.7962	4.4561	0.3401
23	25.3734	24.2517	1.1217
	162.5336	**158.2094**	**4.3242**

Table 9 week8, 10-11am, demanded power =135.3562MW

Gen	Gen End	Retail End	Loss
1	0.0000	0.0000	0.0000
2	0.0000	0.0000	0.0000
7	115.0000	112.9333	2.0667
13	1.8833	1.8406	0.0426
15	1.0641	1.0192	0.0449
16	1.8776	1.7922	0.0855
18	1.7491	1.6467	0.1025
21	1.9295	1.8213	0.1082
22	2.4796	2.3046	0.1750
23	12.5571	11.9984	0.5586
	138.5402	**135.3562**	**3.1840**

Table 10 week52, 2-3pm, demanded power =154.8787MW

Gen	Gen End	Retail End	Loss
1	0.0000	0.0000	0.0000
2	0.0000	0.0000	0.0000
7	115.0000	112.9082	2.0918
13	4.2993	4.2043	0.0949
15	1.7595	1.6810	0.0785
16	3.4742	3.3190	0.1553
18	3.2333	3.0466	0.1867
21	3.2648	3.0760	0.1888
22	4.4665	4.1513	0.3152
23	23.5244	22.4923	1.0321
	159.0220	**154.8787**	**4.1433**

Table 11 week8, 4-5pm, demanded power = 139.5860MW

Gen	Gen End	Retail End	Loss
1	0.0000	0.0000	0.0000
2	0.0000	0.0000	0.0000
7	115.0000	112.9284	2.0716
13	2.3468	2.2955	0.0513
15	1.2167	1.1649	0.0518
16	2.2305	2.1308	0.0997
18	2.0774	1.9574	0.1200
21	2.2231	2.0982	0.1249
22	2.9182	2.7137	0.2045
23	14.9507	14.2970	0.6537
	142.9634	**139.5860**	**3.3774**

Table 12 week52, 7-8pm, demanded power = 159.8748MW

Gen	Gen End	Retail End	Loss
1	0.0000	0.0000	0.0000
2	0.0000	0.0000	0.0000
7	115.0000	112.9007	2.0993
13	5.0324	4.9184	0.1140
15	1.9340	1.8461	0.0879
16	3.8701	3.6953	0.1748
18	3.6008	3.3912	0.2096
21	3.5987	3.3878	0.2109
22	4.9601	4.6074	0.3527
23	26.2953	25.1279	1.1674
	164.2913	**159.8748**	**4.4165**

Table 13 week8 9-10pm, demanded power = 117.0267MW

Gen	Gen End	Retail End	Loss
1	0.0000	0.0000	0.0000
2	0.0000	0.0000	0.0000
7	109.2287	107.2832	1.9455
13	0.6528	0.6449	0.0079
15	0.5033	0.4856	0.0178
16	0.8180	0.7891	0.0289
18	0.7627	0.7257	0.0370
21	0.8985	0.8548	0.0437
22	1.1033	1.0355	0.0678
23	5.3934	5.2080	0.1854
	119.3608	**117.0267**	**2.3341**

The same procedure is repeated for summer weeks, where week 20 and week 28 were used, with the same pattern of hourly demands employed for the winter weeks to generate the coefficients, shown in *Table 14* overleaf.

Table 14 Order of data picked for coefficient generation for summer weeks

Hour\Week	20	28	Hour\Week	20	28
12-1 am	98.52227	91.35701	noon-1pm	152.4016	141.3179
1hr -2hr	92.36462	85.6472	1hr-2hr	153.941	142.7453
2hr-3hr	89.2858	82.79229	2hr-3hr	153.941	142.7453
3hr-4hr	89.2858	82.79229	3hr-4hr	149.3228	138.463
4hr-5hr	86.20698	79.93738	4hr-5hr	147.7834	137.0355
5hr-6hr	89.2858	82.79229	5hr-6hr	147.7834	137.0355
6hr-7hr	98.52227	91.35701	6hr-7hr	143.1652	132.7532
7hr-8hr	116.9952	108.4864	7hr-8hr	141.6258	131.3257
8hr-9hr	133.9287	124.1884	8hr-9hr	141.6258	131.3257
9hr-10hr	146.244	135.6081	9hr-10hr	143.1652	132.7532
10hr-11hr	152.4016	141.3179	10hr-11hr	133.9287	124.1884
11-noon	153.941	142.7453	11hr-12hr	110.8375	102.7766

4.2.2.1 Generator's Contribution to a Retailer's Demand at the Receiving End

The relationship being learnt is the generator's contribution to a retailer's demand at the receiving end. For the IEEE 24 bus system with 10 generators and 10 samples with 4 samples as base case, there are $10 \times (10 - 4) = 70$ of α_1, β_1 and γ_1 respectively, totalling up to 210 coefficients for one relationship under study. Since the trends of the coefficients are the subject under study, they are plotted on 3 graphs for representation purposes illustrated below:

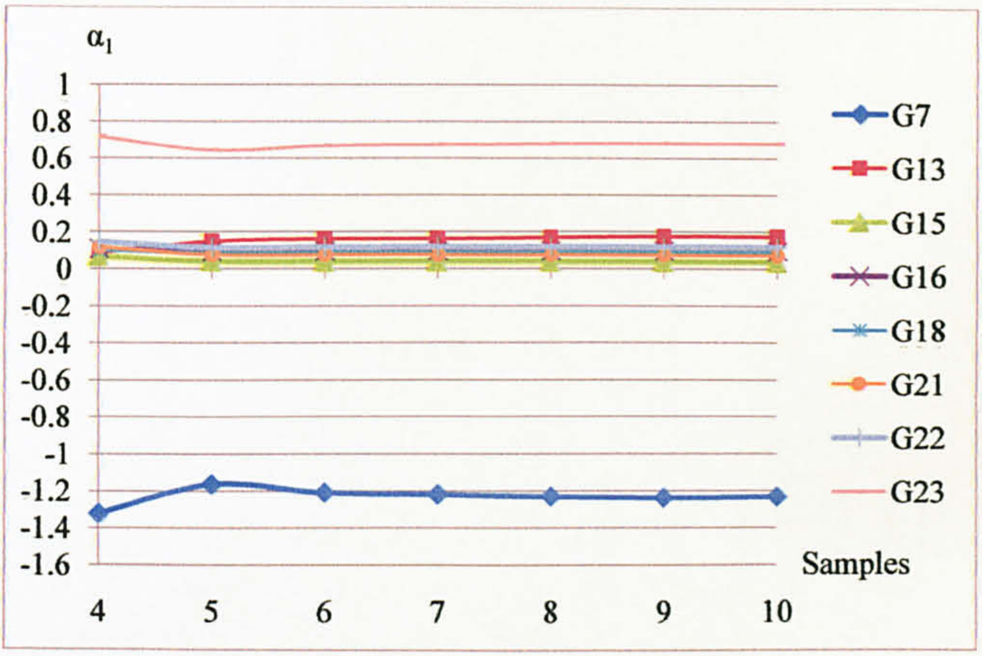

Figure 9 α_1 vs. samples – winter weeks

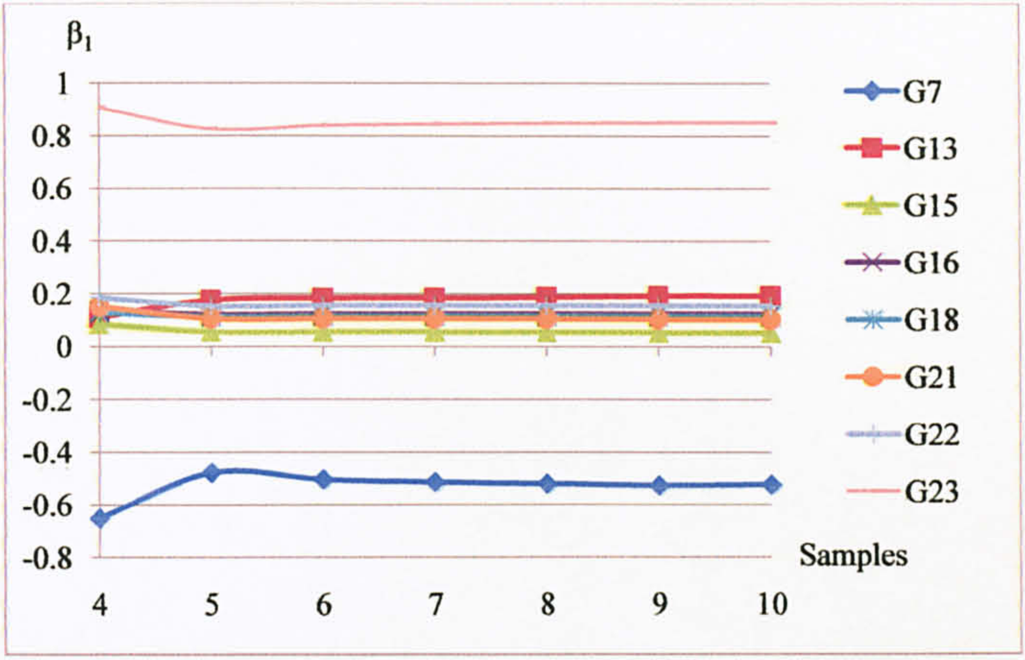

Figure 10 β_1 vs. samples – winter weeks

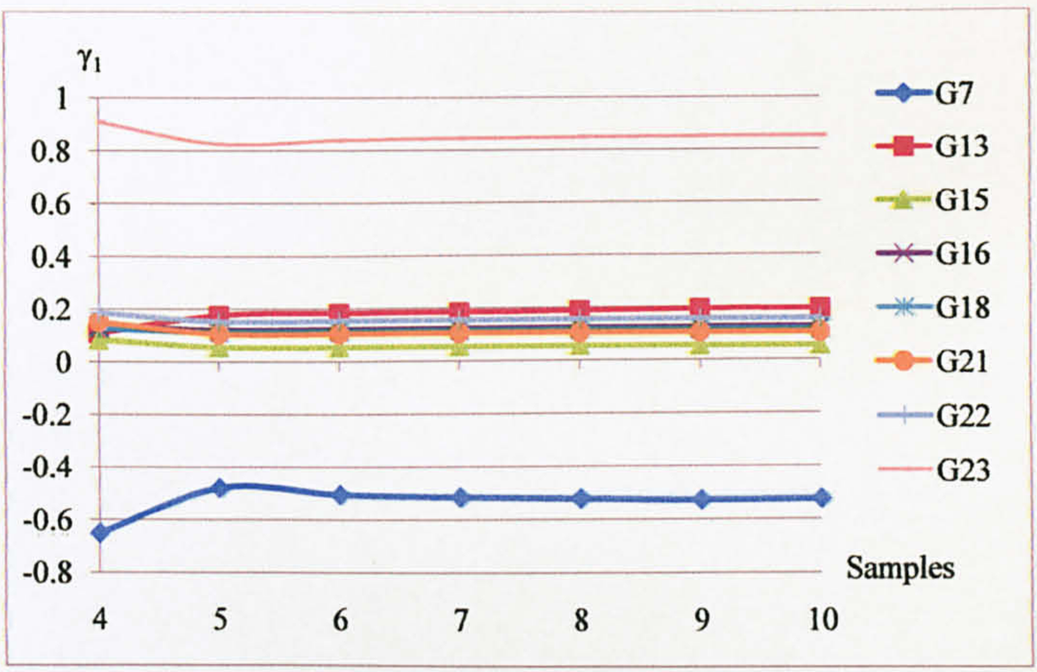

Figure 11 γ_1 vs. samples – winter weeks

The number of trends on a single graph (*Figure 10, 11, 12* respectively) is equivalent to the number of generators supplying load 8. This translates to 8 trends in each graph, with each generator having 3 trends: one for α_1, β_1 and γ_1 respectively. Notice that all trends converge with increasing number of samples. Using the values of α_1, β_1 and γ_1 at the point of ten samples to predict the generator's contribution to a retailer's demand at the receiving end, the results obtained is highly accurate with deviation from the actual results, obtained from load flow by only a mere 0.03%. Hence the better the representation of data/samples are, the more precise the prediction will be.

The trends and magnitude of the coefficients provide information pertaining to the response of generators in the system to increase in demand. Generators with diminutive contribution to the demanded power have near zero coefficients, while generators with larger contribution, notably generators 7 and 23 have greater magnitude, either positively or negatively. This provides an indication to the respective contribution of the generators in supplying the demand of a load.

Closely examining trends of several generators, particularly generator 23 and 13 reveals a very imperceptible up tending trend before flattening out with increase in sample, shown in the series of figures below by using the trends of β_2.

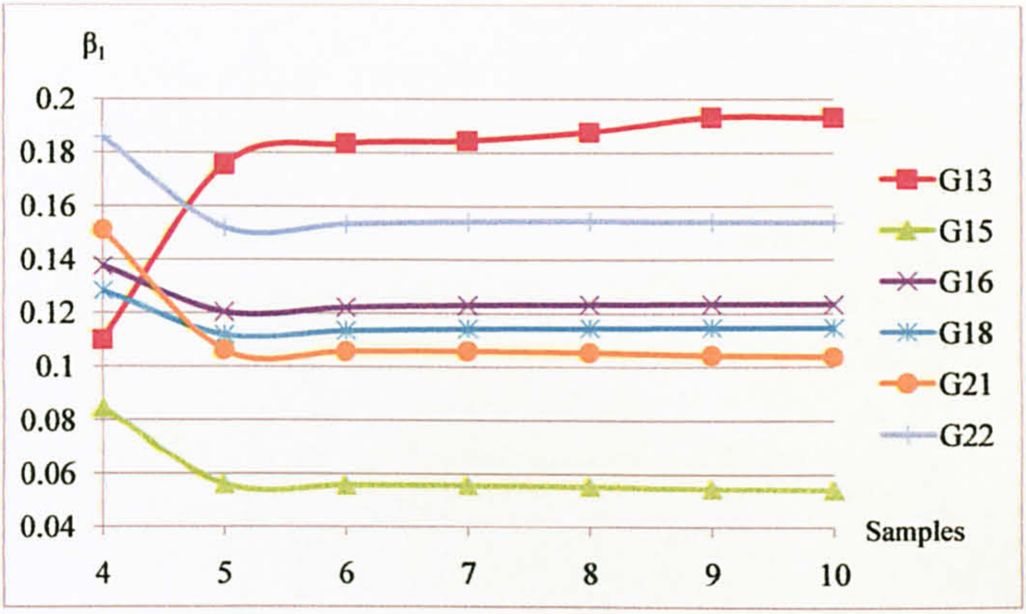

Figure 12 Trend comparison of G13 – winter weeks

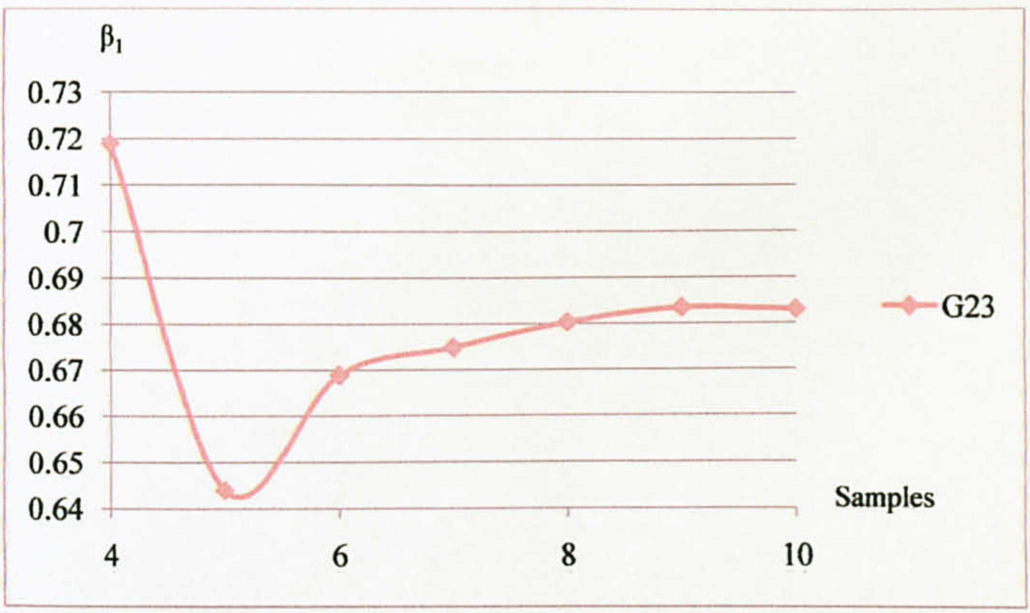

Figure 13 Up scaled trend of G23 – winter weeks

Returning to the schematic diagram of the IEEE 24 bus RTS, it is observed that both these generators are in the closest proximity to bus 8, which naturally becomes the first choice of power source for a marginal increase in demand. Increase of power demanded is regarded on a marginal basis and so is the cost of delivery. From the tracing results (*Tables 4 to 13*) presented above, G13 is observed to have a greater contribution in meeting the marginal increase in demand, particularly in *Table 12* where contribution of G13 begins to surpass G22. Shown below are the tracing results of imaginary demand at bus 8 to establish the hypothesis put forward.

Table 15 Tracing results for demanded power of 170MW

Gen	Gen End	Retail End	Loss
1	0	0	0
2	0	0	0
7	115	112.8840806	2.115919368
13	6.664264808	6.503272562	0.160992246
15	2.283396662	2.175353722	0.10804294
16	4.65734992	4.440914891	0.216435029
18	4.330980423	4.073348781	0.257631642
21	4.266156932	4.008867603	0.257289329
22	5.94304572	5.512194954	0.430850766
23	31.86071076	30.40196685	1.458743905
	175.0059052	**170**	**5.005905225**

Table 16 Tracing results for demanded power of 200MW

Gen	Gen End	Retail End	Loss
1	0	0	0
2	0	0	0
7	115	112.821844	2.178155965
13	12.66351538	12.28327129	0.380244092
15	3.288441067	3.112850184	0.175590882
16	6.880626381	6.525289055	0.355337326
18	6.388503501	5.97602191	0.412481591
21	6.17652348	5.768176571	0.40834691
22	8.728006674	8.049752679	0.678253996
23	47.91617547	45.46279427	2.453381198
	207.041792	**200**	**7.041791959**

While G7 has attained maximum operating limit at 115MW, it can be deduced that the sole reason G13 begins to contribute more to meeting the demand of load 8 is due to the lower marginal loss incurred, in comparison to G22. G23 remains as the primary contributor in meeting the marginal increase in demand; attributed to the overall low transmission loss of G23 supplying load at bus 8 (Relationship of loss will be discussed in detail in the following section). Relating this to the trends of the coefficients, the mentioned properties of G13 and G23 is reflected on the curves of G13 and G23 which is identified with the upward trend before flattening out. The magnitude of the coefficients reveals the contribution, with larger coefficient values corresponding to greater contribution by that particular generator (as presented in the case of G13 and G22).

Thus it can be said that a non converging trend of the coefficients indicates the effect of a change in generation level has on the generation level of the particular generator. The degree of change can be measured through the slope of the curve. The same analysis can be done disregard of the season. Shown below are the trends for summer weeks (week 20 and 28):

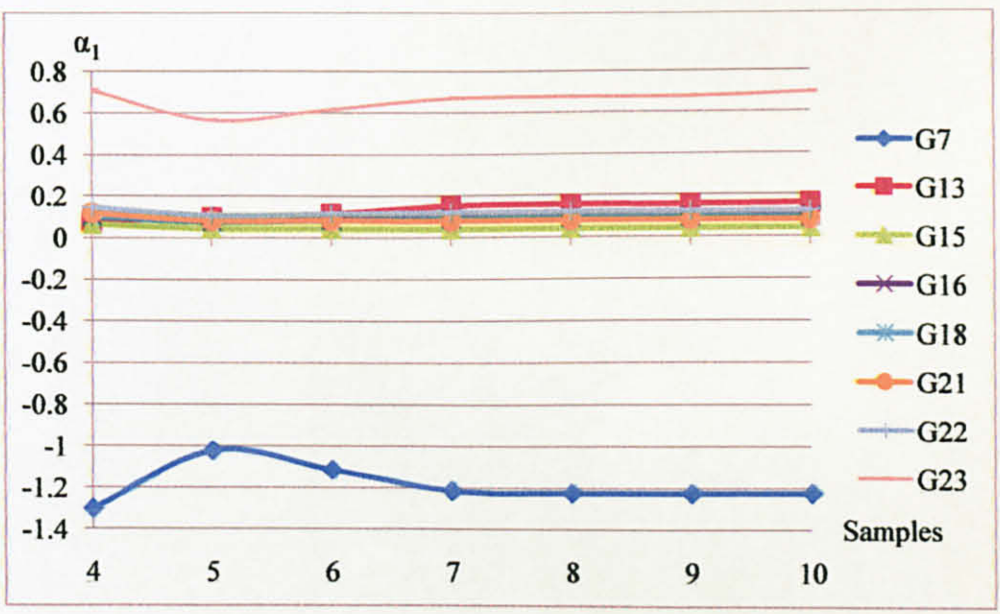

Figure 14 α_1 vs. samples – summer weeks

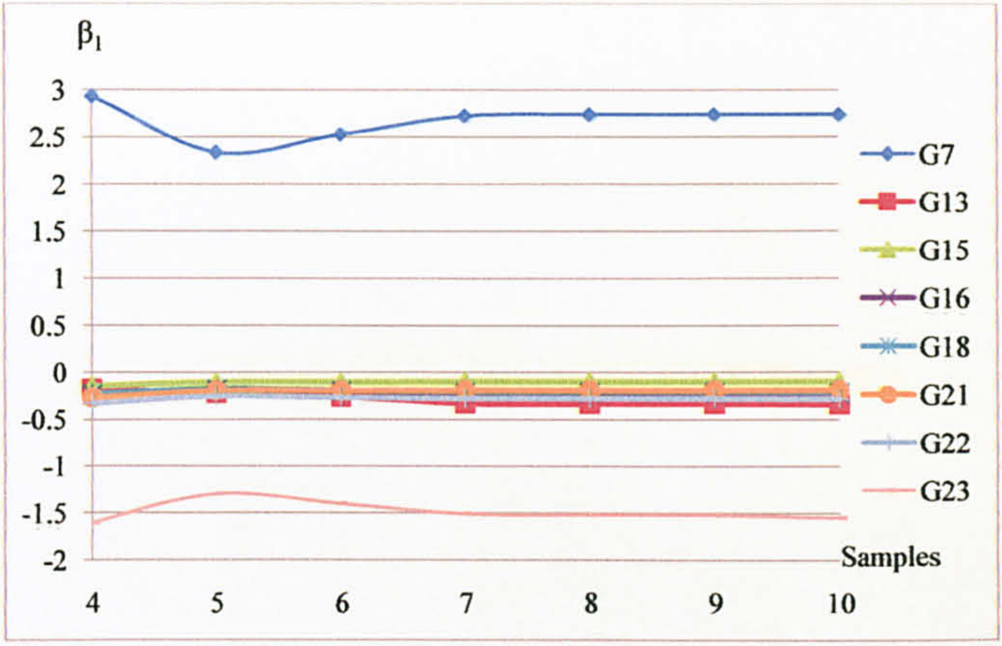

Figure 15 β_1 vs. samples – summer weeks

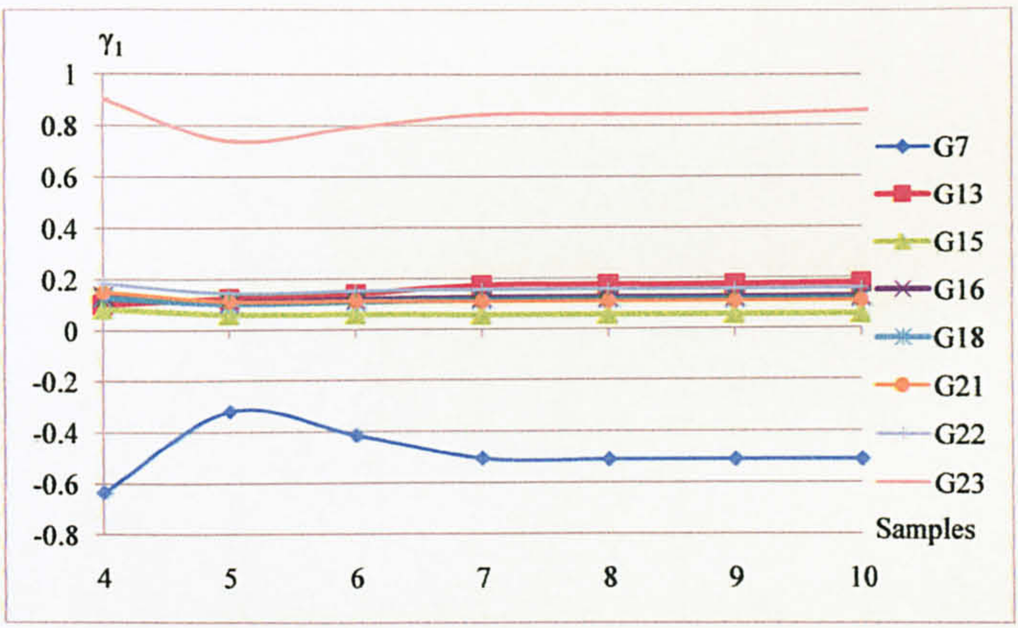

Figure 16 γ_1 vs. samples – summer weeks

Similar trends are observed for the set of summer weeks, which conforms to those established for winter weeks. Since the same load bus is used for analysis, the trends are expected to be consistent disregard of the season. Further analysing the trends of G13, G22 and G23:

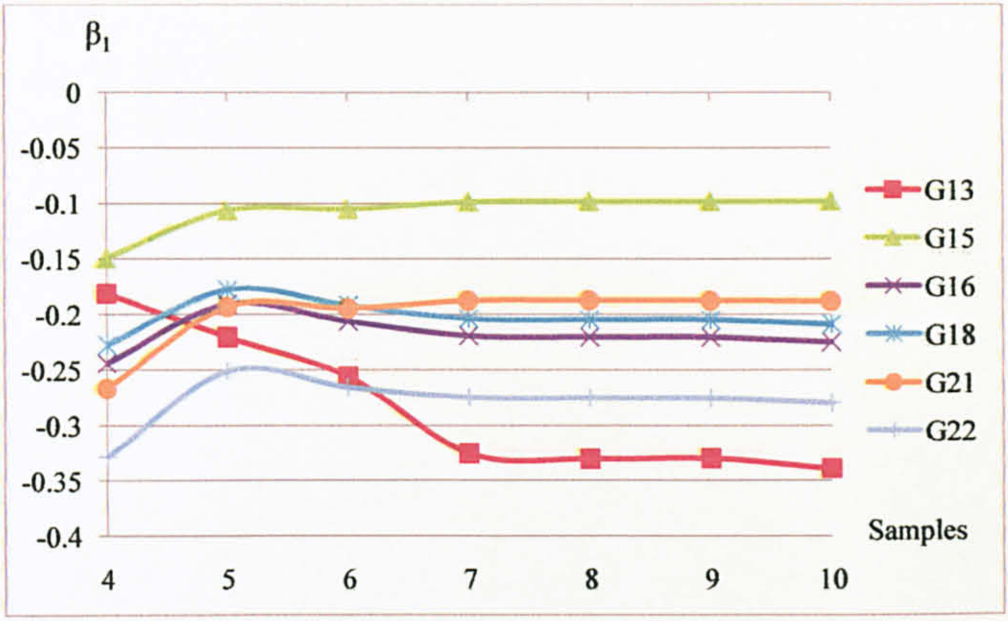

Figure 17 Trend comparison of G13 – summer weeks

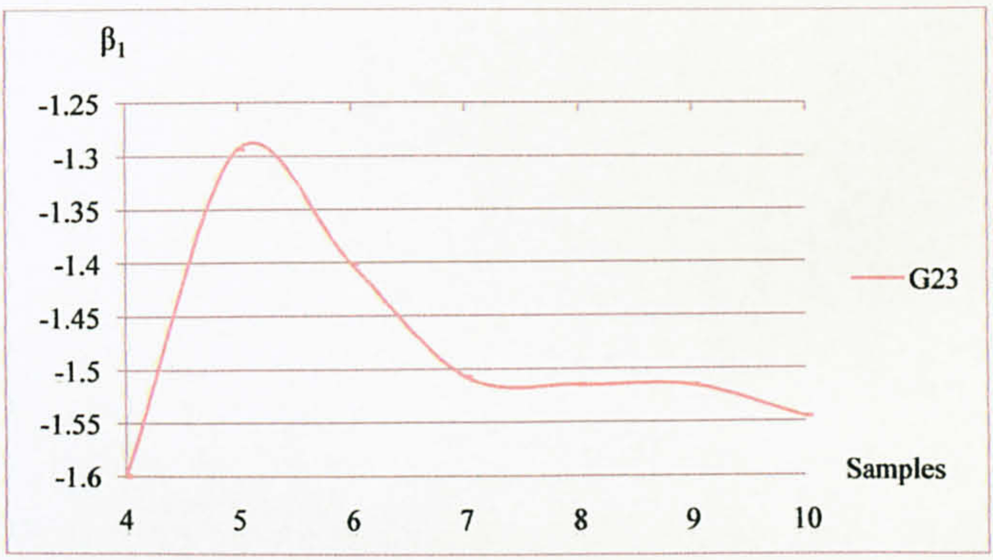

Figure 18 Up scaled trend of G23 – summer weeks

Using the trends of β_1, it could be observed that the same argument could be put forward about the trends as it was for the winter weeks.

4.2.2.2 Retailer's Demand and the Associated Loss in a Transaction

With the same procedure, the 210 coefficients of α_2, β_2 *and* γ_2 are generated and presented in graphical form:

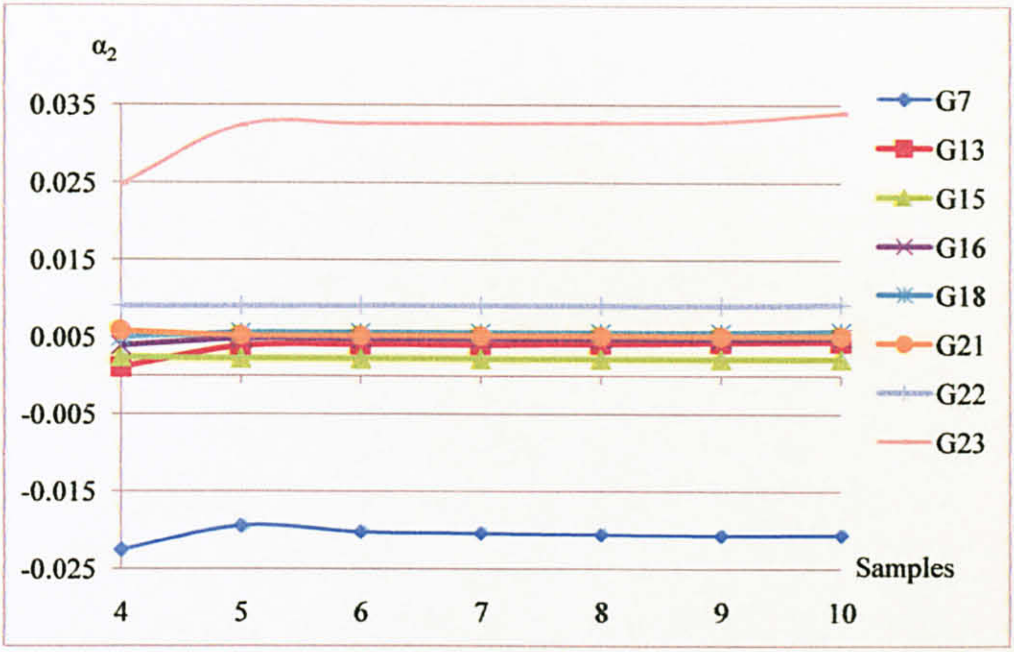

Figure 19 α_2 vs. samples – winter weeks

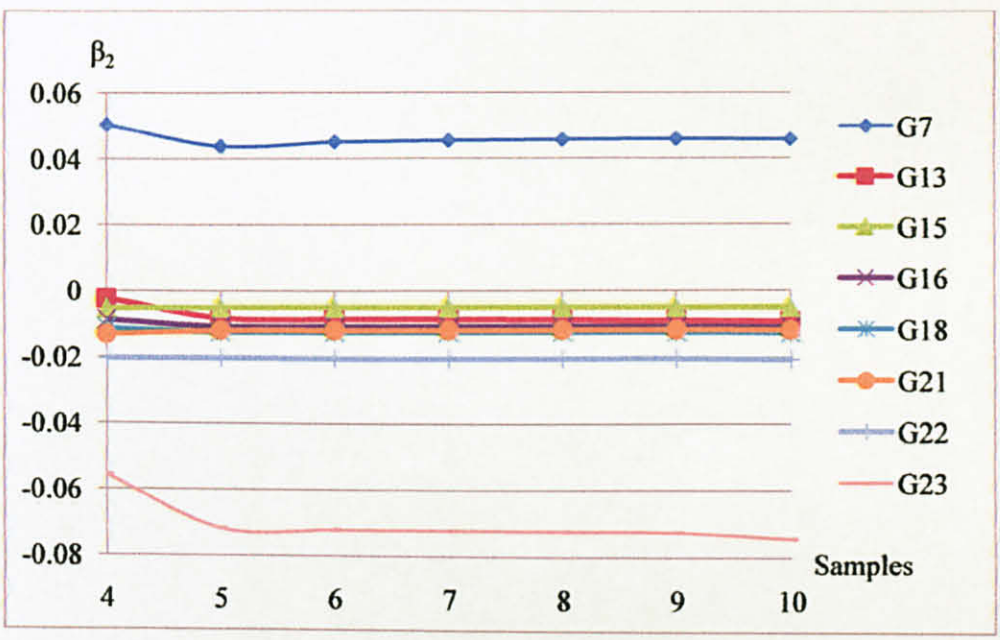

Figure 20 β_2 vs. samples – winter weeks

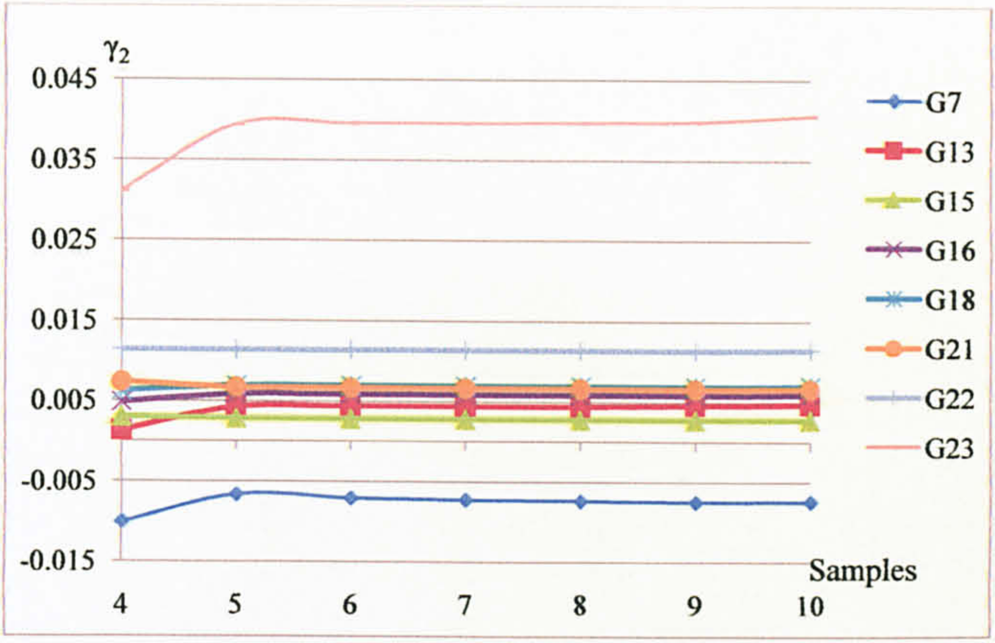

Figure 21 γ_2 vs. samples – winter weeks

A prevailing trend can be observed in *Figure 20, 21, 22*, where the generators with larger contribution notably generators 7 and 23 have greater values, either positively or negatively, while the other generators' coefficients tend to cluster along the zero line. This corroborates with the fact that loss is proportional with power supplied.

Similar to the analysis done in the preceding section, both the magnitude and trends of the coefficients speaks of the loss contribution nature of the generators. The magnitude of the coefficients reflects the magnitude of loss incurred from the transaction supplying load at bus 8. With reference to *Figure 22* above and the tracing results in *Tables 4 to 13*, G7 is seen to be the lowest loss contributor in proportion to the power supplied while G23 is the greatest contributor to losses at bus 8 in proportion to the power supplied.

There is an interesting revelation from the trend of curve G23 (*Figure 20, 21, 22*). The positively (*Figure 20, 22*) or negatively (*Figure 21*) increasing trend indicates a decreasing marginal loss associated to G23 supplying marginal increase in demand of load 8, in spite of the fact that it is the greatest loss contributor.

The arguments are in no way contradicting because G23 may well be the major loss contributor in meeting the demand of load 8; while every increase in unit of power supplied to load 8 (the marginal increase) reduces the overall loss in proportion to the power delivered. This can be seen from the tracing results presented in *Tables 4 to 13*. Further examining the trends of G13 and G22, shown in the figure below, it is seen that G13 has low base loss and low marginal loss in comparison to G22, making it a better choice of power source to supply marginal increase in demand of load at bus 8, than either G22 or G23, despite G23 being the de facto prime power supplier in response to a marginal increase in P_d after G7 reached its operating limits.

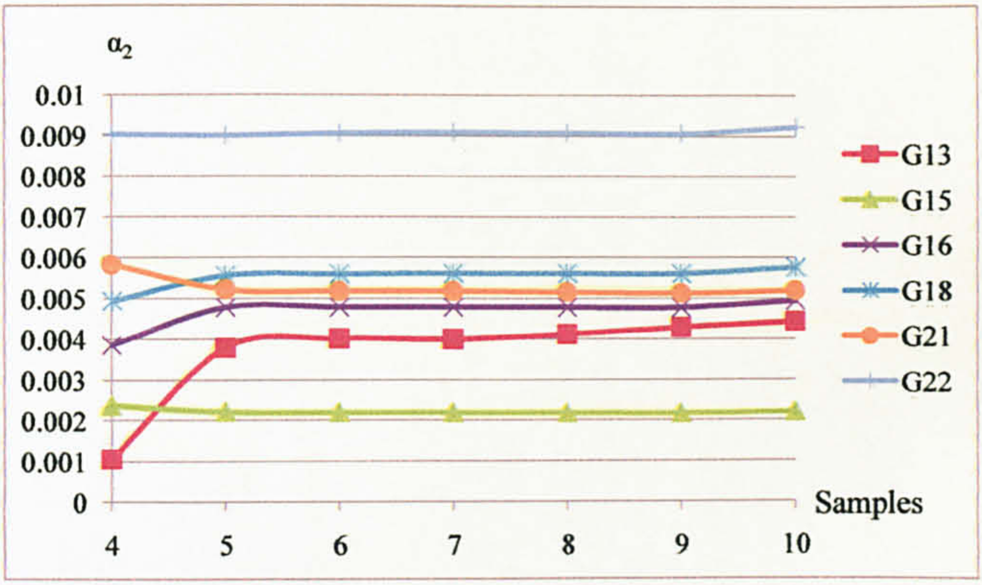

Figure 22 Trend comparison of G13 and G22 to G15, G16, G18 and G21 – winter weeks

This discovery allows the retailers to discern the choice of generators to purchase power from, to supply a marginal increase of demand of a given load, with the function to minimize losses in the transaction, which in turn also minimizes congestion [19]. It would be a discerning economic decision by the retailer to purchase power from generators with low base losses, while purchasing power from generators with low marginal losses to supply marginal increase in demand to harness the lower marginal loss in devising a cost effective power purchasing plan.

Illustrated bellow is an example comparing the transaction losses from two power purchasing arrangements: one without power from G23 and the other with. Assuming that transmission cost is proportional to loss, the choice of power purchasing from generators with low base loss and low marginal loss would minimize losses, thus transmission cost incurred.

Table 17 Comparison of power purchasing arrangement

	Without Power from G23			**With Power from G23**		
Gen	**Gen End**	**Retail End**	**Loss**	**Gen End**	**Retail End**	**Loss**
1	0	0	0	0	0	0
2	0	0	0	0	0	0
7	115.0000	112.9080	2.0920	115.0000	112.9007	2.0993
13	44.0899	42.7118	1.3780	5.0324	4.9184	0.1140
15	0.3362	0.3240	0.0122	1.9340	1.8461	0.0879
16	1.0894	1.0534	0.0361	3.8701	3.6953	0.1748
18	1.0343	0.9861	0.0482	3.6008	3.3912	0.2096
21	0.7190	0.6839	0.0350	3.5987	3.3878	0.2109
22	1.2848	1.2076	0.0772	4.9601	4.6074	0.3527
23	0	0	0	26.2953	25.1279	1.1674
	163.5536	**159.8748**	**3.6788**	**164.2913**	**159.8748**	**4.4165**

The same analysis applies to the trends of coefficients for the summer weeks which are expected to be consistent disregard of the season. The trends are presented in the following three figures:

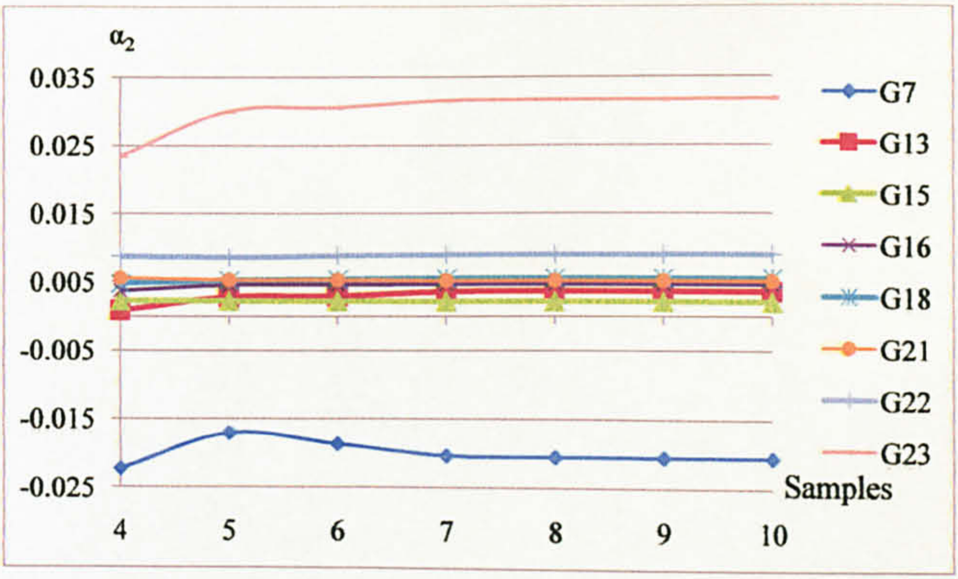

Figure 23 α_2 vs. samples – summer weeks

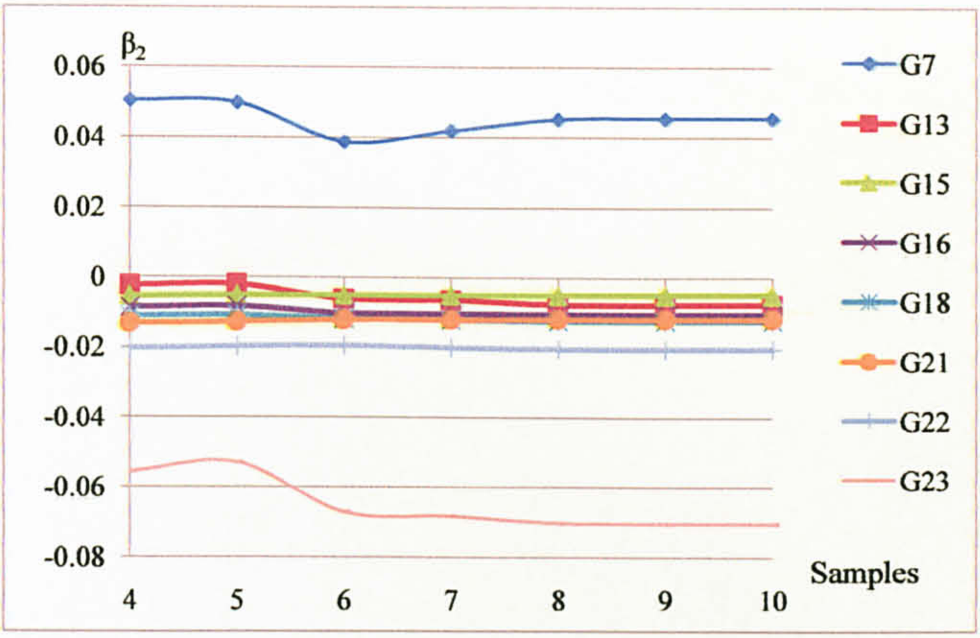

Figure 24 β_2 vs. samples – summer weeks

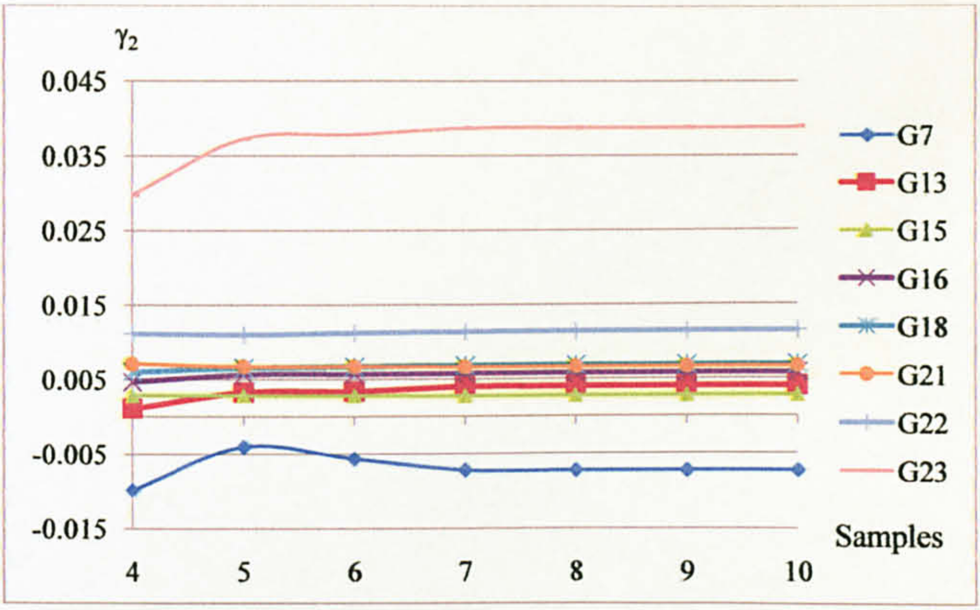

Figure 25 γ_2 vs. samples – summer weeks

Trends of G23 in all three figures are either positively increasing (*Figure 24 & 26*) or negatively increasing (*Figure 25*), but at a much more gradual rate, which implies the reduction in marginal loss with increase in marginal demand. The same is observed for the trends of G13 and G22, shown below in *Figure 27*. Despite the upward trend of G13 and G22, it is also seen to be fairly imperceptible even under a larger scale. This is due to the overall lower demand level in the summer weeks than those of winter weeks as illustrated in *Figure 28*, where the marginal increase in demand for summer weeks does not suffice to harness the reduction of marginal loss in comparison to that of winter weeks.

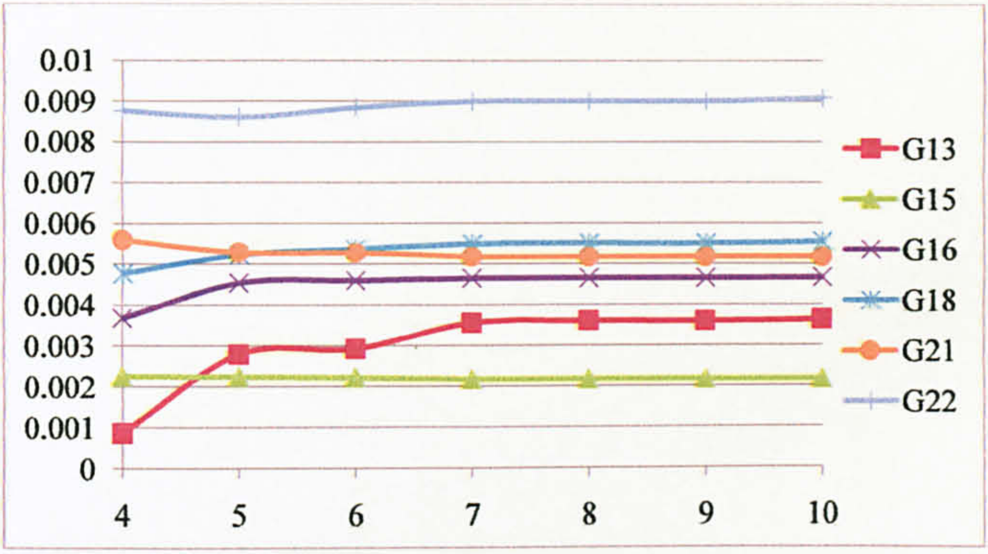

Figure 26 Trend comparison of G13 and G22 to G15, G16, G18 and G21 – summer weeks

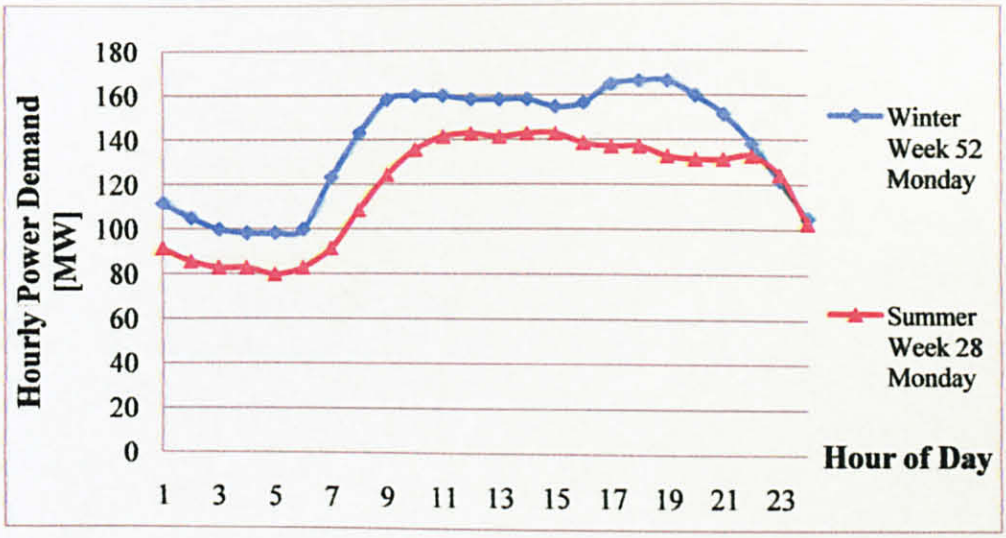

Figure 27 Comparison of hourly demand in winter and summer weeks

4.3 A Proposed Real Time Prediction Algorithm

4.3.1 Performance Evaluation of the Algorithm

A novel prediction method of the oncoming demand on an hourly basis has been devised using the learning coefficients and regression method, along with some statistical tools to meet the acceptance criterion of 10% maximum MAPE given by equation 17 in *Section 3.1* when compared to the hourly demand in [16].

The developed prediction tool is performs short term prediction or short term load forecasting (STLF) [18]. The algorithm is developed from the learning coefficients method, used in conjunction with some statistical tools such as correlation and the rate of change of hourly demand. *Table 18* displays the prediction result on an hourly basis for the Monday of Winter week 52.

Table 18 Prediction results of Monday, Winter week 52

Hour	Prediction [p.u.]	Actual[p.u.]	Error [%]
3	0.9826	0.9992	1.667
4	0.9382	0.9826	4.5198
5	0.9867	0.9826	0.4237
6	1.0092	0.9992	1
7	1.0325	1.2324	16.2162
8	1.4655	1.4322	2.3256
9	1.6543	1.5821	4.5614
10	1.6945	1.5987	5.9896
11	1.7042	1.5987	6.5972
12	1.6099	1.5821	1.7544
13	1.5488	1.5821	2.1053
14	1.5588	1.5821	1.4737
15	1.6099	1.5488	3.9427
16	1.5044	1.5654	3.9007
17	1.5821	1.6487	4.0404
18	1.8263	1.6654	9.6667
19	1.7264	1.6654	3.6667
20	1.5543	1.5987	2.7778
21	1.4267	1.5155	5.8608
22	1.3989	1.3823	1.2048
23	1.2102	1.2157	0.4566
24	1.0214	1.0492	2.6455

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|Actual(i) - Forecast(i)|}{Actual(i)} \times 100 = \frac{86.7966\%}{22} = 3.9453\%$$

The MAPE of the results is below 10% and is within the established acceptance criterion.

The algorithm is also tested on summer weeks to demonstrate the credibility and robustness of the algorithm, shown in the *Table 19* below. The MAPE is found to also fall well within the acceptable range of below 10%.

Table 19 Prediction results of Monday, Summer week 28

Hour	Prediction [p.u.]	Actual[p.u.]	Error [%]
3	0.7994	0.8279	3.4451
4	0.7803	0.8279	5.7521
5	0.8565	0.7994	7.1464
6	0.8108	0.8279	2.0682
7	0.847	0.9136	7.2868
8	1.0753	1.0849	0.8816
9	1.1991	1.2419	3.4451
10	1.4596	1.3561	7.6337
11	1.5217	1.4132	7.6792
12	1.3323	1.4275	6.6659
13	1.3656	1.4132	3.3668
14	1.3656	1.4275	4.3331
15	1.4703	1.4275	3.0016
16	1.475	1.3846	6.5267
17	1.318	1.3704	3.8206
18	1.3133	1.3704	4.1635
19	1.4179	1.3275	6.8073
20	1.299	1.3133	1.0856
21	1.2562	1.3133	4.3447
22	1.3418	1.3275	1.0748
23	1.3941	1.2419	12.2568
24	1.0849	1.0278	5.5590

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|Actual(i) - Forecast(i)|}{Actual(i)} \times 100 = \frac{108.3447\%}{22} = 4.9248\%$$

Despite a slightly higher MAPE, it is still well below 10%, the acceptance criterion. Hence this real time amenable prediction tool, which is capable of producing accurate results in short execution time contributed by the sheer simplicity of the algorithm, is seen to be highly efficient in performing prediction task for a real time system whereby execution and calculation time is of utmost importance for a large system.

4.3.2 Process towards the Establishment of the Algorithm

The procedure begins with a direct adaptation of the learning coefficient method, where the heat rate curve equation, $H(P_G)=\alpha/P_G + \beta + \gamma P_G$ was used to perform prediction by adapting it to the form $P_{new}=\alpha/P_{old} + \beta + \gamma P_{old}$ with P_{new} representing the oncoming power demand and P_{old} the previous hour's demand. This direct adaptation did not yield satisfactory results because the oncoming power has no whatsoever relation to the generation capability of generators, which implies the inaptitude of the equation $P_{new}=\alpha/P_{old} + \beta + \gamma P_{old}$ for prediction purposes. Hence despite large number of samples utilised in generating the coefficients, results obtained had large error percentage.

Next, a thorough study was conducted to identify the key working principle of the method. The logic of the learning coefficient method was extricated, which is as such: the fundamental principle of the method is to obtain a polynomial function, by solving for the coefficients of the polynomial as an approximation to an arbitrary curve, formed by the several sample points on the curve, which then after, prediction is merely an extrapolation using the generated polynomial.

From this juncture, the prediction method of the oncoming demand for the next hour utilising previous hours' demands is begun by examining the hourly demands of week 52 Monday using the data presented in [16]. The sole reason to why the particular day and week is chosen is for consistency to that selected for the trend analysis of the learning coefficient. It was observed that an order 5 polynomial approximated the curve as illustrated:

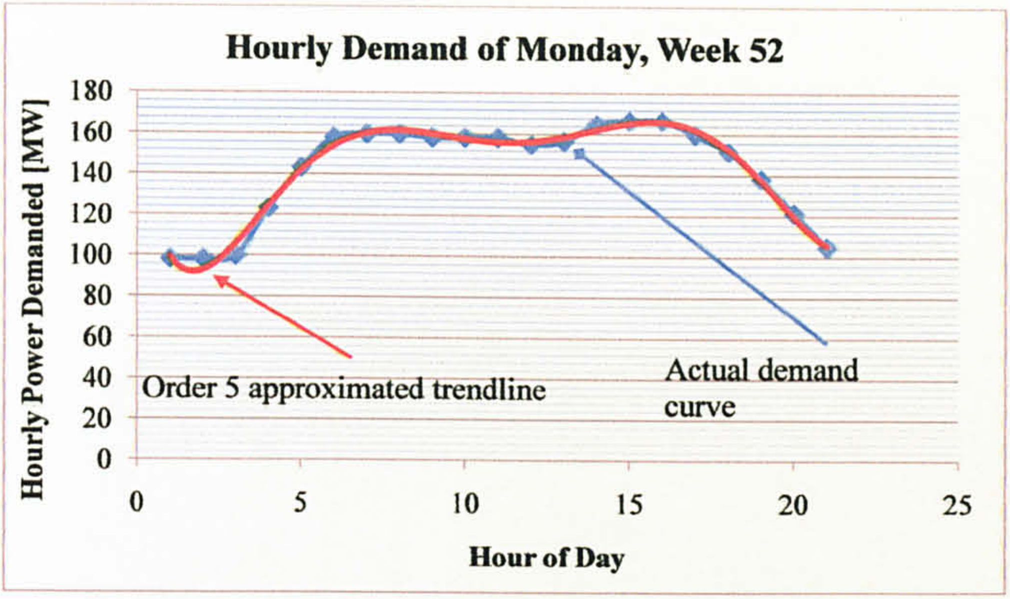

Figure 28 Graph of hourly demand for Monday week 52 and the approximating trend line

The same is done for the Monday of week 28 of the summer week, which led to the same finding of an order 5 polynomial approximation to the curve.

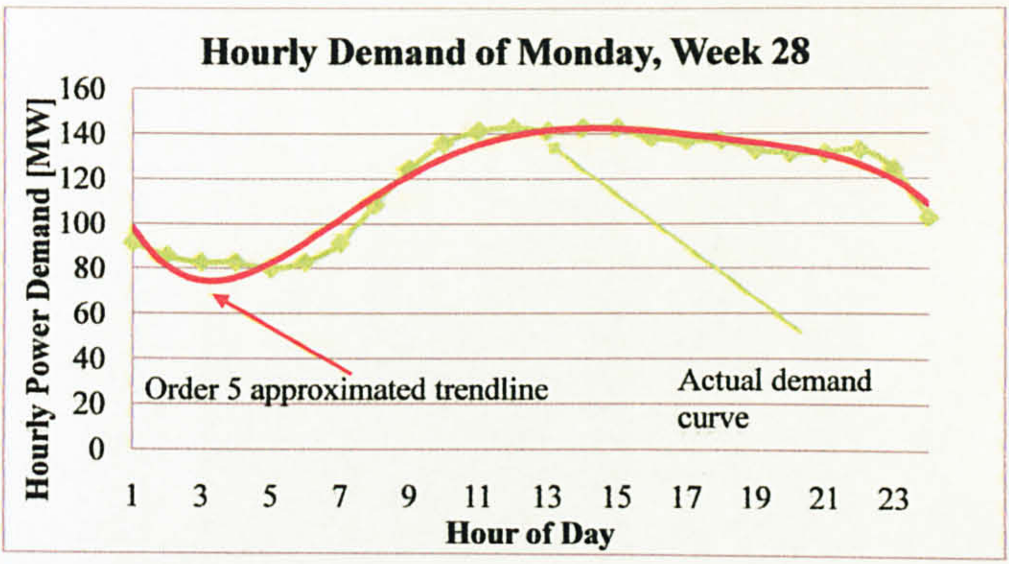

Figure 29 Graph of hourly demand for Monday week 52 and the approximating trend line

This hypothesis is done by assuming that the hourly demand data in [16] is drafted from credible sources, which qualifies the use of the data for modelling and simulation purposes. Now, a redefined method is to also generate coefficients of a 5[th] order polynomial of the form $P_{new} = \alpha P_{new}^5 + \beta P_{old}^4 + \gamma P_{old}^3 + \delta P_{old}^2 + \varepsilon P_{old} + \lambda$ by using the regression method. The gist of the method is to accumulatively use all data from previous hours to generate the coefficients, aimed at achieving minimal prediction error with increasing number of samples.

However after exhaustive testing of the method, it was found that the approximation with an order five polynomial produced extremely erratic results, with extremely large prediction error for certain hours of the day. This setback is attributed to the fact that an order five polynomial approximates the hourly demand curve as a whole, with all known 24 points on the curve. Using an order five polynomial to perform prediction for any of the intermediary hours (hours 2 to 23) is excessive when a lower order polynomial would have sufficed. Also it was noticed that accuracy of prediction is not guaranteed with a good polynomial fit. A review of the polynomial approximation method in MATLAB's Help corroborates this fact, by further mentioning that the desired fit of the polynomial approximation depends entirely on the purpose of the approximation, whereby a good fit does not necessarily produce superior results.

The conclusion drawn from the previous attempt was to cap the maximum order of polynomial at five, while the possibility of using lower order polynomials when predicting intermediary hours (hours 2 to 23) is examined. In a real power system operating scenario, the oncoming demand is usually affected by the demand of preceding hours, to a certain extent. Evoking this fact, the method of using correlation of rate of change of demand in determining the optimal order of polynomial was conceived, drawn from the hypothesis that power demand at hour 9 of the day may not have any relation to the power demand at hour 20 of the similar day.

Only highly correlated rate of change of demand to the immediate preceding hour's rate of change of demand is qualified as a sample point. The maximum allowable degree of the generated polynomial is contingent upon the number of available sample points: polynomial order = available samples – 1, i.e. an order three polynomial would require at least 4 data (points on the curve) to generate a unique set of coefficient. Since the maximum allowable order of polynomial was mentioned above to be five, the corresponding maximum number of samples is capped at six. This combined method now forms the prediction tool described in *Section 4.3.1*.

It has to be pointed out that human analysis is imperative in performing prediction. This algorithm is only a tool to aid decision making and is not to be relied solely on without any analysis.

4.4 The Integrated Prediction Tool

All developed sub routines were integrated to form a prediction programme, the programme utilises the predicted oncoming demand and the learning coefficients to obtain the estimated generation level of all generators in the system with their associated losses. The trends of the coefficients can also be displayed if desired. Displayed below is the MATLAB Command Window printout when the programme is executed.

MATLAB Command Window

```
Week of the day to be predicted ->52

Hour of the day to be predicted ->16

Prediction for hr 16,wk 52= 1.5044 @ 3.9007 percent of error

Hit any key to continue

 1.Trends for Pgd
 2.Trends for Loss_t
 3.Display nothing
 Enter choice of trends to be displayed: 3

 Estimation for oncoming Load at bus 8
          L8 = 150.437715 MW
 --Gen--   --Gen End--   --Loss--
              [MW]          [MW]
     1        0.0000        0.0000
     2        0.0000        0.0000
     7      115.1794        2.0893
    13        3.7645        0.0821
    15        1.5923        0.0700
    16        3.0902        0.1366
    18        2.8761        0.1646
    21        2.9436        0.1685
    22        3.9885        0.2794
    23       20.9005        0.9069
              -----         -----
            154.3350        3.8973
```

Figure 30 Prediction results for Monday week 52, hour 16

CHAPTER 5
CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Comparing the Upstream and the Downstream algorithms to the newly derived Sending and Receiving Algorithm, it was observed that more information were revealed from the analysis and were able to be picked out at ease. Simplification of the method also contributes to the reduction in computation steps and time, since execution can be done with minimal programming.

Converging trend of the learning coefficients underpins the learning coefficient method in performing prediction, where given sufficient samples and spread of samples, prediction done for an oncoming demand could be done to a highly accurate degree. Other valuable information from the trends if harnessed would aid as an effective decision making tool in optimization of profit and operation in a deregulated market, for both generator company and retailer.

The proposed prediction programme is amenable to real time implementation and has been extensively proven to perform well within established standards. It has been demonstrated the capability of the prediction tool to perform prediction with MAPE of below 5%, lower than the 10% threshold which was considered good. The sheer simplicity of the concept employed in developing the prediction tool gives it an edge in execution time, which is seen to be relatively shorter and quick.

5.2 Recommendation

More studies are to be conducted to extend the now capable of performing hour ahead prediction with lead-time of 1 hour to also perform day ahead prediction with lead-time less than 24 hours [18]. Also, the programme is to be tested with actual load demand data to further enhance its credibility. Further prospect on reducing the MAPE to a more stringent 3% is also envisioned to be greatly beneficial.

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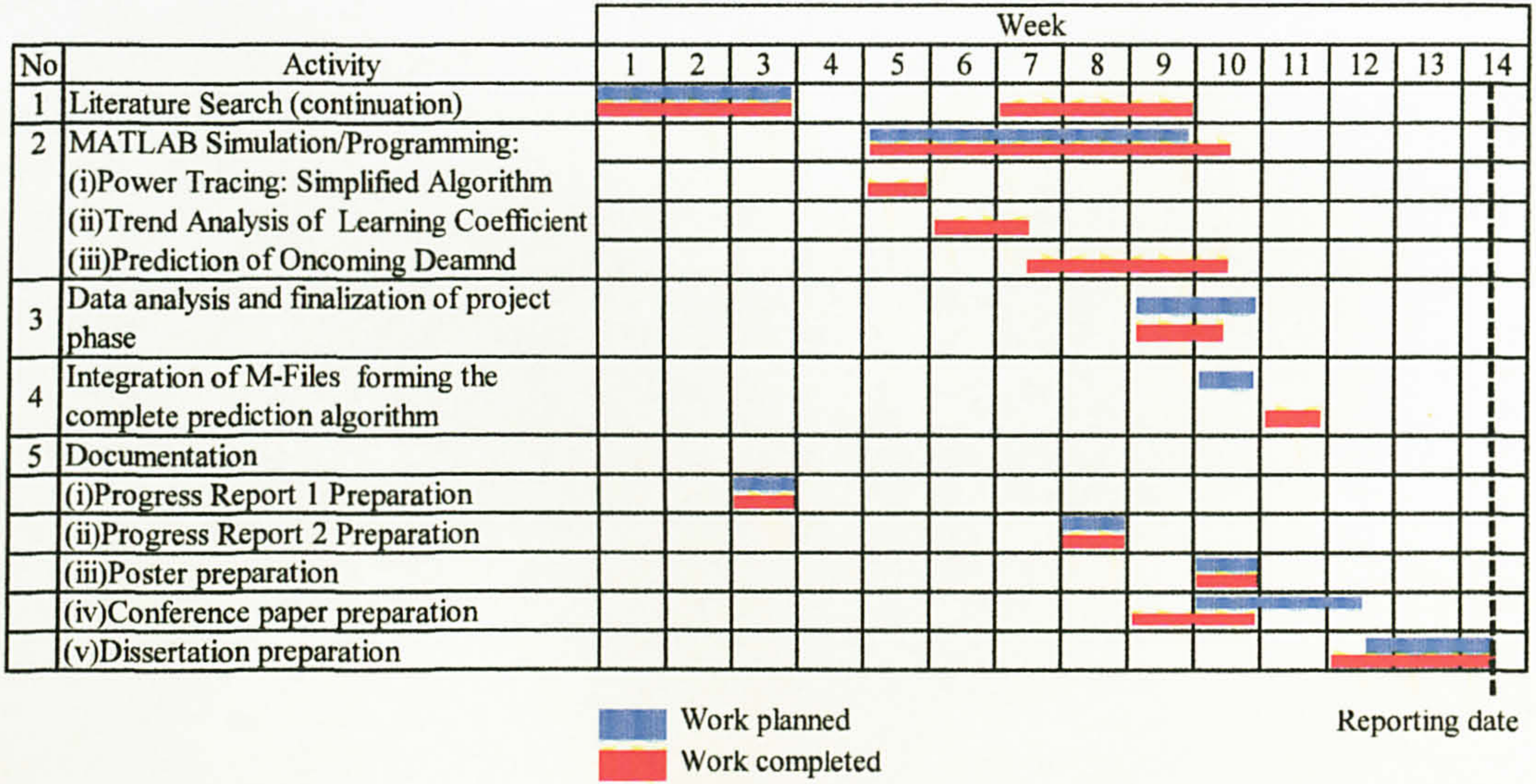
APPENDICES

APPENDIX A

PROJECT GANTT CHART



APPENDIX B
CODING DOCUMENTATION

run_this2

This main programme is to be run to execute the complete prediction process. Generator and bus data are input is this part of the programme. It starts by performing prediction for the desired hour and week. Prediction results along with the corresponding error will be printed and waits for user prompt to proceed with the execution. Upon receiving the prompt, the programme will calculate and display the tracing breakdown for the predicted hour, based on the prediction result and internally generated learning coefficients to perform the calculation.

prediction2

As the name suggests, this subroutine performs the prediction function by first calculating the rate of change of previous hours' rate of change of demand. The correlation of the rate of change is then calculated to determine the number of samples (past hour demand data) to be used for the prediction of the desired hour. The number of samples are capped at six to maintain a maximum order of five polynomial used for approximation.

The order of polynomial to be used for approximation is contingent upon the number of samples used, where order = samples – 1. Regression is then performed to generate the coefficient. This is done by using the *polyfit* function of MATLAB. The sample points are scaled to ensure that coefficients generated are unique. As of date, the data contained in this sub routine is data for Monday week 48 to 52 and week 1 to week 5. This data section has to be changed with relevant data of day and week of the year for prediction of that specific time.

flow_tracingprep_bus8_2

This programme performs load flow using the Newton-Rhapson method and preliminary data preparation for power tracing. Load bus in interest is prompted for with the corresponding change in load, which for convenience sake; the programme has been slightly modified to use bus 8 by default. This sub routine is amenable to systems of various sizes apart from the current IEEE 24 bus system. Only required changes are branch and bus data.

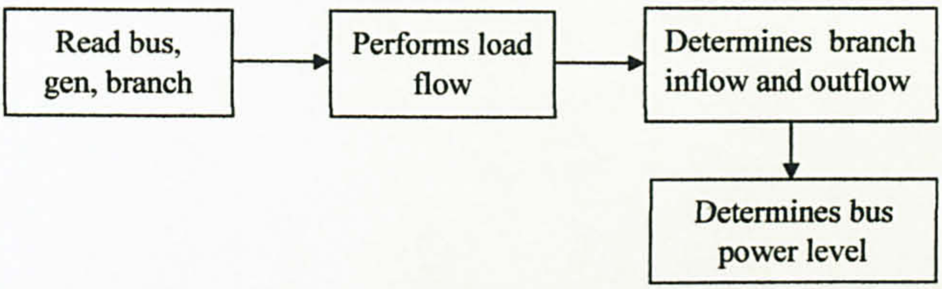


Figure 31 Flow chart of *flow_tracingprep* subroutine

tracing_and_store

This subroutine performs the tracing function and all related loss apportioning and extent of use of line calculations for all the sample points selected from *prediction2*. The programme displays only relevant results to the load bus entered in *flow_tracingprep_bus8_2*. For example a simulation performed with load at bus 8 under scrutiny, only the loss apportioning of load 8 and extent of use of line serving bus 8 will be displayed. This feature will avoid cluttering of the results screen and information overload to allow quick analysis and viewing of results.

Results are compiled into a single matrix and then disintegrated into three matrices: generation end power, retail end power, loss. All elements of the matrices are in p.u. These results are stored to be passed to the *learningcoeff2* subroutine for generation of the coefficients.

Key to effective data manipulation in this subroutine is the appending of matrix. Each set of data from one sample is contained in one large matrix by appending the consecutive sets of data to the current matrix.

One set of data from one sample is a 10×4 matrix, hence the final data matrix dimension will be $10 \times (4 \times no.of\ samples)$, with each $1 + 4n$ column being the generator id, column $2 + 4n$ being the power delivered from generator's end, column $3 + 4n$ the power received at load's end and column $4 + 4n$ the loss incurred in that transaction. In such indexing manner, like data are extracted and stored in 3 distinct matrices: *Pgenend*, *Pretailend* and *Ploss*.

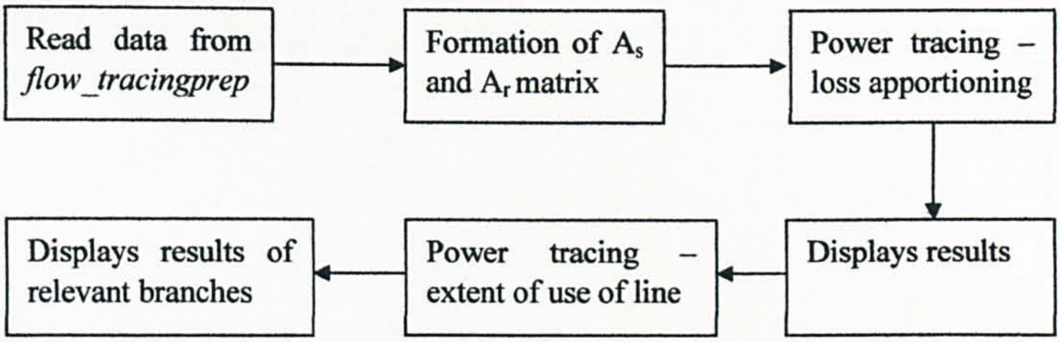


Figure 32 Flow chart of *tracing_up_down* subroutine

Learningcoeff2

Learning coefficients are calculated for a given day in a season. $\alpha, \beta\ and\ \gamma$ are matrices with dimension of $(no.of\ gen) \times (samples - 3)$. Logic behind the $(samples - 3)$ is attributed to the fact that the coefficients are calculated with 4 cases as the base, hence matrix indexing has to account for that.

As of yet, this sub routine only solves for one complete set of learning coefficients (α, β *and* γ) related to one of the four relationships under examination described in *section 2.5* of *Literature Review* for a given day in a given season. A 'complete' set of learning coefficients constitutes of $(no. of\ gen) \times (samples - 3)$ values of α, β *and* γ respectively. 3 graphs are plotted as the final result being α vs. samples, β vs. samples and γ vs. samples, with each graph individually having $(no. of\ gen)$ curves plotted on the same axis.